

# MSc Data Mining

## Topic 01 : Module Overview

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### Part 04 : A Review of Statistical Concepts

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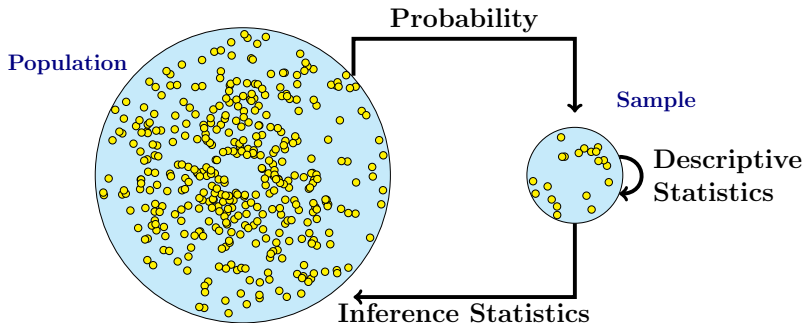
#### Outline

- Type of Data
- Descriptive statistics
- Probability in five minutes (probably)

# Part I

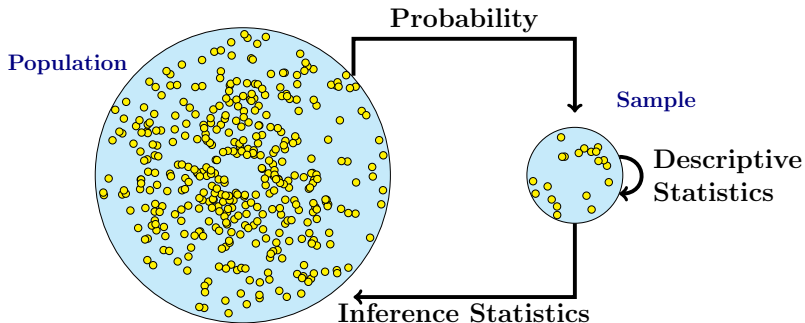
## Fundamental Concepts

# “Central Dogma” of Statistics



- The **population** is the group of all items of interest.
  - Frequently very large or even sometimes infinite.
  - Population attributes are called **population parameters**.
- A **sample** is a subset of the population drawn from the population.
  - Potentially very large, but usually of orders smaller than the population.
  - Sample attributes are called **sample statistics**.

# “Central Dogma” of Statistics



- **Descriptive Statistics** is a set of methods of organising, summarising, and presenting data in a convenient and informative way.
- **Inferential statistics** is a set of methods, to draw conclusions or inferences about characteristics of populations based on data from a sample.

So we use the **sample statistics** to make inferences about the **population parameters**

# Descriptive vs Inference Statistics

We use sample statistics to make inferences about population parameters.

- Therefore, we can make an estimate, prediction, or decision about a (unknown) population based on (known) sample data.

## Rationale

- Large populations make investigating each member impractical and expensive.
- Easier and cheaper to take a sample and make estimates about the population from the sample.

## Warning

Such conclusions and estimates are not always going to be correct. For this reason, we build into the statistical inference “measures of reliability” namely confidence level and significance level.

— **even when all of the assumptions made in constructing the sample are true!.**

# How good is your data?

## Validity

A **valid** measurement is one which actually measures what it claims to measure.

- Unemployment figures are validly measured using the Labour Force Survey not the Live Register

## Reliability

A **reliable** measurement is one which will give approximately the same result time after time, when taken on the same individual or object.

- Most physical measurements are reliable, for example measuring your weight using a bathroom scales.
- Some measurements may be reliable but not necessarily valid.
  - Are exams reliable measuring devices?
  - Are exams results valid measurements of intelligence?

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# How good is your data?

## Bias

Sometimes when measurements are made a systematic error is made which underestimates or overestimates the true value. Such a measurement is called a **biased** measurement.

- Suppose your bathroom scales always overestimated your weight.
- Car speedometers are deliberately biased to overestimate a car's real speed.

## Variability

Some datasets are more variable than others.

- A dataset consisting of the ages of 100 students in WIT will be less variable than a dataset consisting of the ages 100 randomly chosen Irish people.

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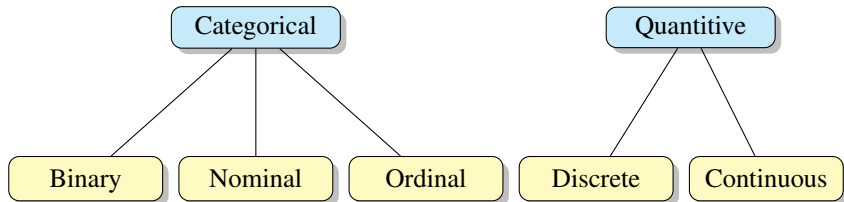
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# Types of Data



2 Categories

TRUE/FALSE  
YES/NO,  
etc

More Categories

Gender,  
Religion,  
Favourite Team, etc

Order matters

Numerical

**CAN** be repre-  
sented by integers  
on the number lineNumber of students  
in this class

+ Uninterrupted

Takes values from  
intervals on the  
number lineDuration of this  
class

Cannot order

Cannot add / subtract / multiple or divide

# Dimensionality of Data Sets

We will frequently use a table to represent our data:

- Each row represents a **observation** / **subject** / **case**.
  - Univariate** — single measurement per subject.
  - Bivariate** — two measurements per subject.
  - Multivariate** — Multiple measurements per subject.
- Each column represents a **variable** / **attribute**.
  - Each variable is then Binomial/Nominal/Ordinal/Discrete/Continuous

## Tips dataset

`df.head(10)`

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4
5	25.29	4.71	Male	No	Sun	Dinner	4
6	8.77	2.00	Male	No	Sun	Dinner	2
7	26.88	3.12	Male	No	Sun	Dinner	4
8	15.04	1.96	Male	No	Sun	Dinner	2
9	14.78	3.23	Male	No	Sun	Dinner	2

`df.shape`

(244, 7)

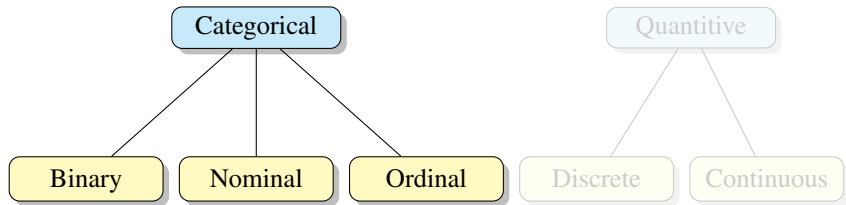
`df.dtypes`

```
total_bill    float64
tip           float64
sex           category
smoker        category
day           category
time          category
size          int64
dtype: object
```

## Part II

# Analysing Categorical Data

# Types of Data — Categorical Data



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YES/NO,  
etc

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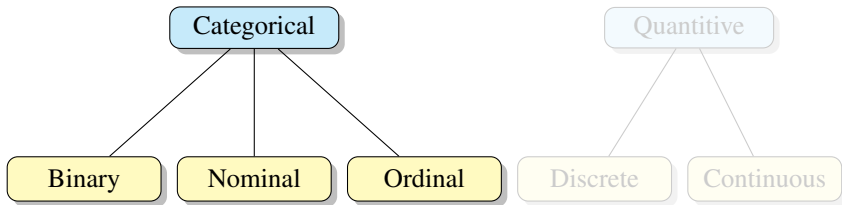
Cannot add / subtract / multiple or divide



Limited to methods that only deal  
with counts/frequencies



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## Graphical Methods

- Bar chart
- Pie chart

## Numerical Methods

- Frequency counts
- Number of unique values



⇒ Limited to methods that only deal with counts/frequencies



# Example: tips.day

```
df.day.nunique()
```

4

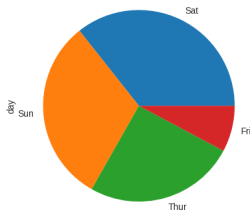
```
df.day.value_counts()
```

```
Sat    87
Sun    76
Thur   62
Fri    19
Name: day, dtype: int64
```

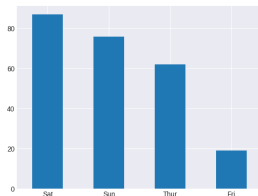
```
df.day.describe()
```

```
count    244
unique      4
top       Sat
freq       87
Name: day, dtype: object
```

```
df.day.value_counts().plot(kind='pie');
```



```
df.day.value_counts().plot(kind='bar')
plt.xticks(rotation=0);
```



These are horrible visualisations — pie chart does not show counts, and what about the category order in the bar charts

# Comments

- Pie charts are often over used (especially by newspapers) but they have significant limitations:
  - Comparing two pie charts is problematic since people find it harder to compare angles to lengths.
  - If one uses relative frequencies (or percentages) then the number of observations needs to be clearly stated.
  - Should not be used if the number of categories is large.

*To my mind, the best use of a pie chart is when you have one value that is overwhelmingly larger than the rest and you don't want the audience to focus on the actual values, but just bamboozle them with the overwhelming size of the leading segment. Of course, this seems to come close to embracing the old adage, "There are lies, damn lies and statistics."*

— [www.juiceanalytics.com/writing/writing/the-problem-with-pie-charts](http://www.juiceanalytics.com/writing/writing/the-problem-with-pie-charts)

## See also

- [www.edwardtufte.com/bboard/q-and-a-fetch-msg?msg\\_id=00018S](http://www.edwardtufte.com/bboard/q-and-a-fetch-msg?msg_id=00018S)  
(Edward Tufte is a statistician and author of 4 books on data visualisation.)
- “Save the Pies for Dessert” article at [www.perceptualedge.com/articles/08-21-07.pdf](http://www.perceptualedge.com/articles/08-21-07.pdf)

## Part III

# Analysing Quantitative Data

# Types of Data — Quantitative Data

## Graphical Methods

- Histogram — for shape, spread
- Boxplot — for shape, location, outliers
- ...

## Numerical Methods

- mean, median — centre
- standard deviation, range — spread
- z-scores, quantiles — location
- ...

YES/NO,  
etc

Religion,  
Favourite Team, etc

Cannot order

Cannot add / subtract / multiple or divide

## Quantitative

Discrete

Continuous

Numerical

**CAN** be represented by integers on the number line

Number of students in this class

Numerical+Uninterrupted

Takes values from intervals on the number line

Duration of this class

Can add / subtract / multiple and divide (even for discrete data)

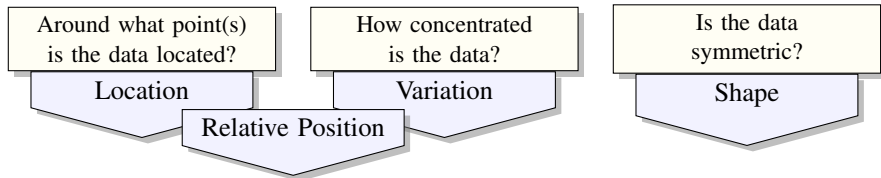
# Numerical Methods for Quantitative Data

Around what point(s)  
is the data located?

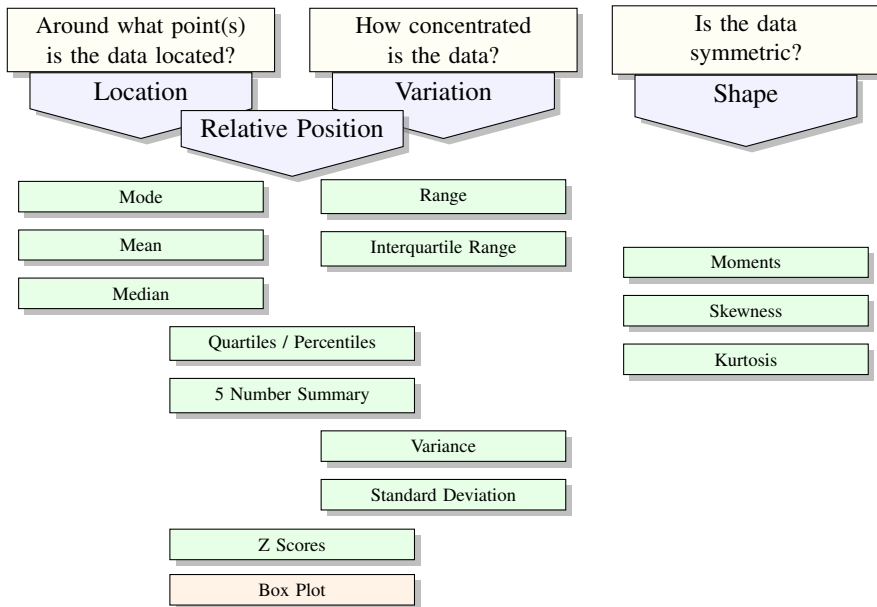
How concentrated  
is the data?

Is the data  
symmetric?

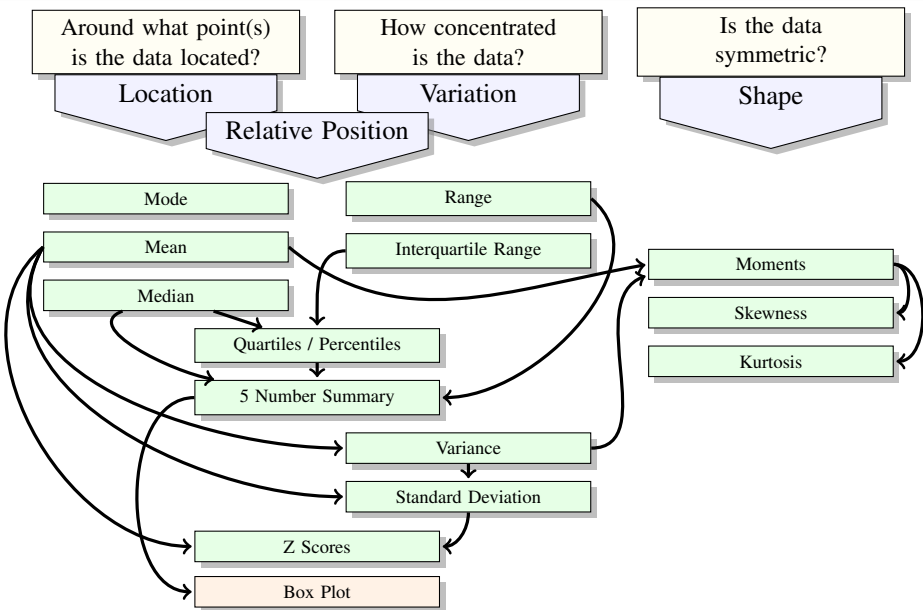
# Numerical Methods for Quantitative Data



# Numerical Methods for Quantitative Data



# Numerical Methods for Quantitative Data





# Measures of Central Tendency

A **measure of central tendency** is a single value that attempts to describe a set of data by identifying the central position within that set of data.

- Often called **measures of central location**.
- The **mode**, **mean**, and **median** are common\* measures of central tendency, but under different condition, some measures of central tendency become more appropriate to use than others.



\*Wikipedia lists 14 measures, [https://en.wikipedia.org/wiki/Central\\_tendency](https://en.wikipedia.org/wiki/Central_tendency)

# Mode vs Mean vs Median

## Metrics

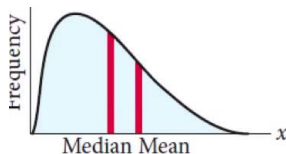
- The **(arithmetic) mean** is the sum of its data values divided by data count.
- The **median** is the point in the variable that splits the values in two equal groups.
- The **mode** is the most frequently occurring value in a variable.

## Comparison

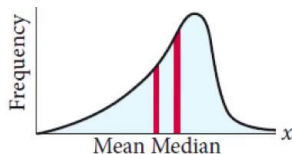
- If variable is nominal then mode is your only option.
- If variable is ordinal then you can use either mode or median.
  - The median only makes use of the order information in the variable (i.e., which numbers are bigger), but doesn't depend on the precise numbers involved. Hence median can be applicable while the mean is not.
- For quantitative data, either the mean or the median is generally acceptable.
  - Which one to pick depends on the data and what you're trying to achieve. The mean has the advantage that it uses all the information in the data (which is useful when you don't have a lot of data), but it's very sensitive to extreme values.

# Mean vs Median and Shape

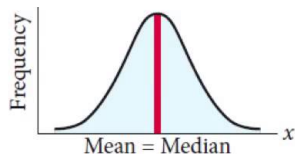
If the distribution is  $\left\{ \begin{array}{l} \text{negatively skewed} \\ \text{symmetric} \\ \text{positively skewed} \end{array} \right\}$  then  $\left\{ \begin{array}{l} \text{mean} < \text{median} \\ \text{mean} = \text{median} \\ \text{mean} > \text{median} \end{array} \right\}$



**(a) Right-Skewed**



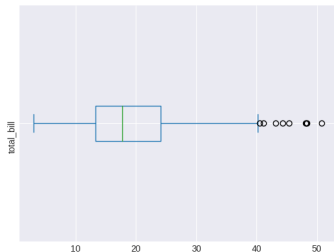
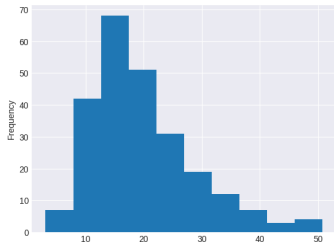
**(b) Left-Skewed**



**(c) Symmetric**

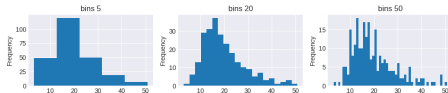
# Histogram and Box-Plot

```
df.total_bill.plot(kind='hist');
```



```
df.total_bill.plot(kind='box', vert=False)  
plt.yticks(rotation=90);
```

- Parameter **bin** controls level of granularity.



Too few ← Number of Classes → Too many

Too much smoothing or not enough detail remaining for summary to be of use.      Too much detail/noisy so main features are difficult to see.

- Distribution is uni-modal
- and right skewed (longer tail to the right)
- Boxplot clearly show outliers (dots), skewness
  - Centre line is the median
  - Box edges are the first and third quartiles.

# Measures of Variation

Measures of variation measures the amount that values vary or differ among themselves.



- A measure of statistical variation/dispersion is a nonnegative real number that is zero if all the data are the same and increases as the data become more diverse.
- Dispersion is contrasted with location or central tendency, and together they are the most used properties when summarising variables.
- There are different ways of measuring variation:<sup>†</sup> range, variance and standard deviation

---

<sup>†</sup>Wikipedia lists over 12 measures,  
[https://en.wikipedia.org/wiki/Statistical\\_dispersion](https://en.wikipedia.org/wiki/Statistical_dispersion)

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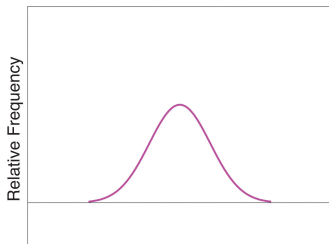
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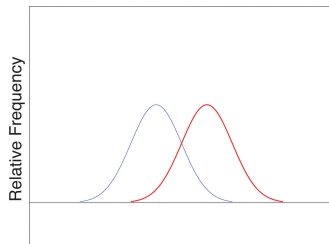
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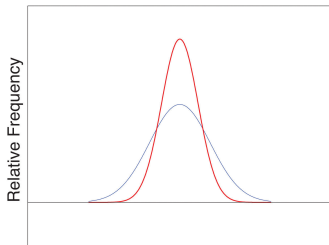
# Central Tendency (Location) vs Variation



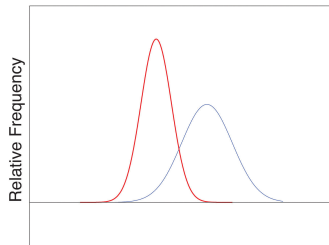
(a) Two Identical Sets



(b) Locations Differ



(c) Variabilities Differ



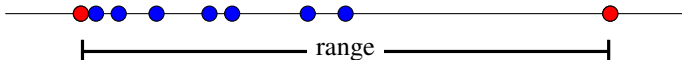
(d) Locations and Variabilities Differ

# Measures of Variation Metrics

## Range

The **range** of a data set is the difference between the maximum and minimum values in the set.

- ✓ Simplest to calculate and has easy interpretation, and only two values are used in its calculation.
- ✗ The range is highly sensitive to outliers (in fact it depends exclusively on the extreme values).



## Variance

The **variance**,  $\sigma^2$ , where  $\sigma$  is the **standard deviation** and is defined as follows

$$\sigma^2 = \sum_{k=1}^n \frac{(\bar{x} - x_k)^2}{n} \quad (1)$$

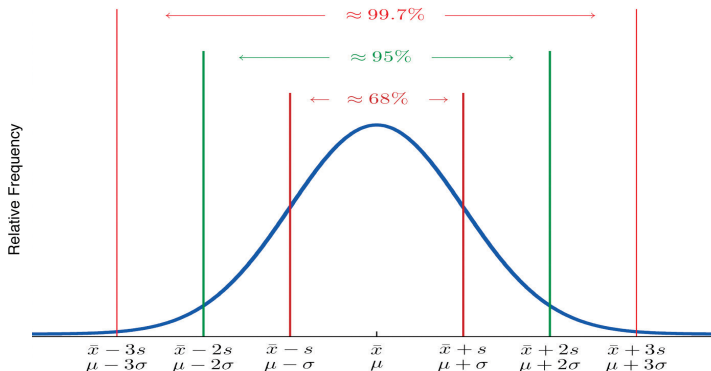


# Interpreting and Understanding Standard Deviation

## **Property: Empirical rule for data with a Bell-shaped distribution**

If the variable has a bell-shaped distribution, then

- About 68% of all values fall within 1 standard deviation of the mean.
- About 95% of all values fall within 2 standard deviation of the mean.
- About 99.7% of all values fall within 3 standard deviation of the mean.



# Measures of Shape

---

Finally we look symmetric, and how "peaked" the set of data is:

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- We start with a reference distribution — the **standard normal curve**.



Standard Normal Curve

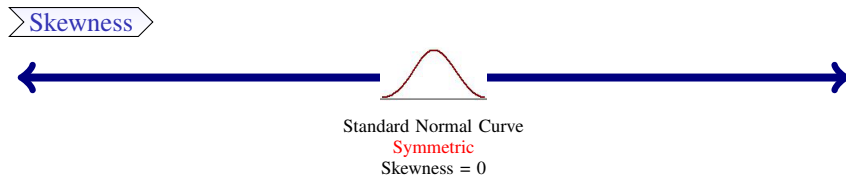
**Symmetric**

Skewness = 0

# Measures of Shape

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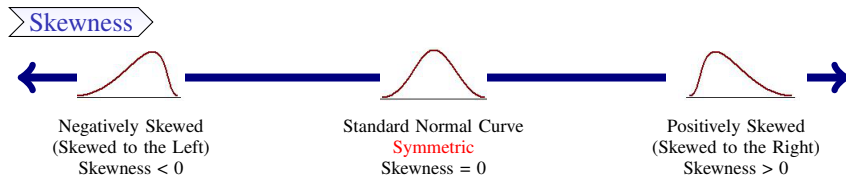
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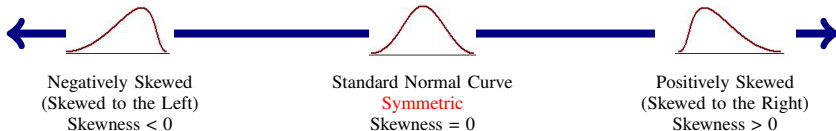


# Measures of Shape

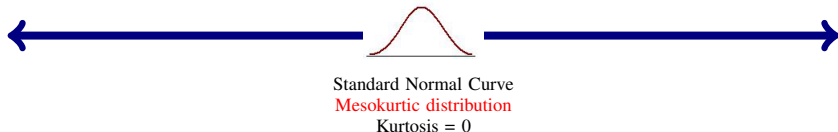
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- **Skewness** is a measure of how symmetric the distribution is.
- **Kurtosis** is a measure of how peaked the distribution is.

## Skewness



## Kurtosis

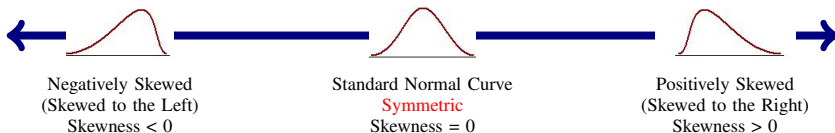


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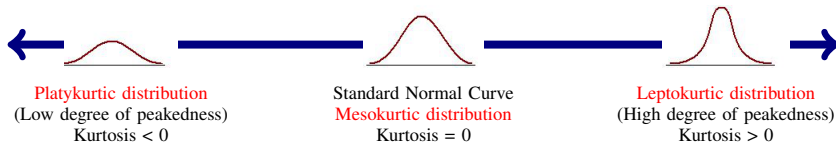
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- **Kurtosis** is a measure of how peaked the distribution is.

## Skewness



## Kurtosis



# Outliers

- An **outlier** is an observation which does not appear to belong with the other data.
- Outliers can arise because of a measurement or recording error or because of equipment failure during an experiment, etc..
- An outlier might be indicative of a sub-population, e.g. an abnormally low or high value in a medical test could indicate presence of an illness in the patient.





# Detecting Potential Outliers

There are many criteria for identifying<sup>‡</sup> outliers, all have issues. We will adopt the criteria:

*Points that are beyond the quartiles by one-and-a-half IQR's will be deemed **potential** outliers.*

## Detecting Potential Outliers

**STEP 1** Determine,  $Q_1$  and  $Q_3$ , the first and third quartiles.

**STEP 2** Determine IQR, the interquartile range.

**STEP 3** Determine the **lower** and **upper fences**

$$\text{LIF} = Q_1 - 1.5 \times \text{IQR} \quad \text{UIF} = Q_3 + 1.5 \times \text{IQR}$$

Points beyond these fences are potential **outliers**.

---

<sup>‡</sup>Automatic removal of outliers is very dangerous. Google "automatic removal of outliers ozone" and see [www.math.uni-augsburg.de/htdocs/emeriti/pukelsheim/1990c.pdf](http://www.math.uni-augsburg.de/htdocs/emeriti/pukelsheim/1990c.pdf)

# Part IV

## Probability

# Concept: Probability

## Definition 1 (Probability)

**Probability** is a measure of the likelihood or chance that a particular event would occur. It is given as a number in the range 0 to 1.

- Informal interpretation ...



- Other scales can be used such as

odds (e.g. 1:10 for 10% probability)

or a log scale (e.g. 10<sup>-1</sup> to 10<sup>0</sup>)

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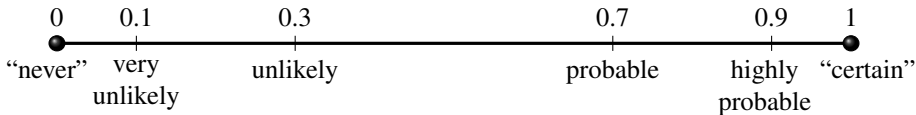
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- Informal interpretation ...



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  - odds for (betting, medicine)

$$\text{odds for} = \frac{\text{probability}}{1 - \text{probability}} \iff \text{probability} = \frac{(\text{odds for})}{(\text{odds for}) + 1}$$

- entropy (in machine learning/communication theory) uses scale  $[0, \infty)$

$$\text{entropy} = (\text{probability}) \times \log_2 \left( \frac{1}{\text{probability}} \right)$$

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29 of 36

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- $$\text{odds for} = \frac{\text{probability}}{1 - \text{probability}} \quad \Longleftrightarrow \quad \text{probability} = \frac{(\text{odds for})}{(\text{odds for}) + 1}$$

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**Probability** is a measure of the likelihood or chance that a particular event would occur. It is given as a number in the range 0 to 1.

- Other scales can be used such as
  - odds for (betting, medicine)

- entropy (in machine learning/communication theory) uses scale  $[0, \infty)$

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# Probability Laws

I

## Probability Law:

If an event,  $E$ , is a particular outcome then  $\Pr(E)$  represents the probability that  $E$  will occur and

$$0 \leq \Pr(E) \leq 1 \quad (2)$$

The sum of the probabilities of all possible outcomes of an experiment equals 1, i.e.,

## Probability Law: (Total Law of Probability)

If  $E_1, E_2, \dots, E_n$  are all the mutually exclusive outcomes of an experiment then

$$\Pr(E_1) + \Pr(E_2) + \dots + \Pr(E_n) = 1 \quad (3)$$

In English — “Some outcome must happen.”

## Probability Law: (Independent Events)

Events  $A$  and  $B$  are **independent** if and only if

$$\Pr(A \text{ AND } B) = \Pr(A) \Pr(B) \quad (4)$$

# Probability Laws

## II

If two events are **mutually exclusive**, then they cannot both happen ...

### Probability Law: (Mutually Exclusive)

If events  $A$  and  $B$  are **mutually exclusive** then

$$\Pr(A \cap B) = \Pr(A \text{ AND } B) = 0 \quad (5)$$

### Probability Law: ('OR'ing events)

If  $A$  and  $B$  are two events then, in general

$$\Pr(A \text{ OR } B) = \Pr(A) + \Pr(B) - \Pr(A \cap B). \quad (6)$$

If  $A$  and  $B$  are mutually exclusive then, from Equation (5),

$$\Pr(A \text{ OR } B) = \Pr(A) + \Pr(B). \quad (7)$$

i.e., **OR**  $\longrightarrow$   $+$

# Probability Laws

## III

### Probability Law: (Classical Probability 1)

If an experiment has  $n$  possible outcomes, with all equally likely, then the probability of any one of these outcomes occurring is  $1/n$ .

Example: Picking a card from a deck of 52 cards

$$\Pr(\text{Picking an ace of hearts}) = \Pr(\text{Picking a 4 of clubs}) = \dots = \frac{1}{52}$$

### Probability Law: (Classical Probability 2))

Given an experiment with each possible outcome equally likely and

$S$  = Sample Space — Set of possible outcomes

$E$  = Desired result — Set of outcomes that give the desired result  
then

$$\Pr(E) = \frac{\#E}{\#S} = \frac{\text{Number of desired outcomes}}{\text{Number of possible outcomes}} \quad (8)$$

# Conditional Probability

Probability values you calculate depend on the information you know (or are given) about related events.

In more mathematical jargon ...

- Suppose we have an event  $A$  with a probability  $\Pr(A)$ .
- We obtain information that a related event  $B$  has occurred.
- We now want to use this information to update our estimate for the probability that  $A$  occurs.

This new probability is written as

Probability Law: (Conditional Probability)

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

“Probability of  $A$  occurring given that  $B$  has occurred.”

# Conditional Probability for Independent Events

Recall: If  $A$  and  $B$  are independent events then

$$\Pr(A \text{ AND } B) = \Pr(A) \Pr(B)$$

Substituting this formula into the conditional probability formula (which is true for all pair of events) we get

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

Hence we have

Probability Law: (Conditional Probability for Independent Events)

If  $A$  and  $B$  are independent events then

$$\Pr(A|B) = \Pr(A) \tag{9}$$

In English “If  $A$  and  $B$  are independent then, knowing that event  $B$  has occurred does not change the probability of event  $A$ .”

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# Conditional Probability for Mutually Exclusive Events

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Probability Law: (Conditional Probability for Mutually Exclusive)

If  $A$  and  $B$  are mutually exclusive then

$$\Pr(A|B) = 0 \tag{10}$$

In English “If  $A$  and  $B$  are mutually exclusive then, knowing that event  $B$  has occurred means that  $A$  cannot occur.”

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# Bayes' Theorem

The conditional probability law states

$$\Pr(A|B) = \frac{\Pr(A \text{ AND } B)}{\Pr(B)} \implies \Pr(A|B) \Pr(B) = \Pr(A \text{ AND } B)$$

and

$$\Pr(B|A) = \frac{\Pr(A \text{ AND } B)}{\Pr(A)} \implies \Pr(B|A) \Pr(A) = \Pr(A \text{ AND } B)$$

Combing the two results we have

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

Hence we have

Probability Law: (Bayes' Theorem)

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

In English “Bayes Theorem allows us to switch the order of terms in a conditional probability”