

# Statistical Inference

## Lecture One

<https://people.bath.ac.uk/masss/APTS/apts.html>

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# Overview of Lecture One

- We wish to consider inferences about a parameter  $\theta$  given a parametric model  $\mathcal{E} = \{\mathcal{X}, \Theta, f_X(x|\theta)\}$

$(\mathcal{E}, x) \xrightarrow{\text{statistician, Ev}} \text{Inference about } \theta.$

- We'll consider a series of **statistical principles** to guide the way to learn about  $\theta$ .
- Weak Indifference Principle, WIP**: if  $f_X(x|\theta) = f_X(x'|\theta)$  for all  $\theta \in \Theta$  then  $\text{Ev}(\mathcal{E}, x) = \text{Ev}(\mathcal{E}, x')$ .
- Distribution Principle, DP**: if  $\mathcal{E} = \mathcal{E}'$ , then  $\text{Ev}(\mathcal{E}, x) = \text{Ev}(\mathcal{E}', x)$ .
- Transformation Principle, TP**: for the bijective  $g: \mathcal{X} \rightarrow \mathcal{Y}$ , construct  $\mathcal{E}^g = \{\mathcal{Y}, \Theta, f_Y(y|\theta)\}$ . Then  $\text{Ev}(\mathcal{E}, x) = \text{Ev}(\mathcal{E}^g, g(x))$ .
- $(\text{DP} \wedge \text{TP}) \rightarrow \text{WIP}$ .

# Introduction

- We wish to consider inferences about a parameter  $\theta$  given a parametric model

$$\mathcal{E} = \{\mathcal{X}, \Theta, f_{\mathcal{X}}(x | \theta)\}.$$

- We assume that the model is **true** so that only  $\theta \in \Theta$  is unknown. We wish to learn about  $\theta$  from observations  $x$  (typically, **vector valued**) so that  $\mathcal{E}$  represents a model for this **experiment**.

Smith (2010) considers that there are **three** players in an inference problem:

- 1 **Client**: person with the problem
- 2 **Statistician**: employed by the client to help solve the problem
- 3 **Auditor**: hired by the client to check the statistician's work

The statistician is thus responsible for explaining the rationale behind the choice of inference in a compelling way.

# Reasoning about inferences

We consider a series of **statistical principles** to guide the way to learn about  $\theta$ . The principles are meant to be either **self-evident** or **logical implications** of principles which are self-evident.

We shall assume that  $\mathcal{X}$  is **finite**: Basu (1975) argues that “infinite and continuous models are to be looked upon as mere approximations to the finite realities.”

- Inspiration of Allan Birnbaum (1923-1976) to see how to construct and reason about statistical principles given “**evidence**” from data.
- The model  $\mathcal{E} = \{\mathcal{X}, \Theta, f_{\mathcal{X}}(x | \theta)\}$  is accepted as a working hypothesis.
- How the statistician chooses her inference statements about the true value  $\theta$  is entirely down to her and her client.
  - ▶ as a point or a set in  $\Theta$ ;
  - ▶ as a choice among alternative sets or actions;
  - ▶ or maybe as something more complicated, not ruling out visualisations.

- Following Dawid (1977), consider that the statistician defines, *a priori*, a set of possible **inferences about  $\theta$**
- Task is to choose an element of this set based on  $\mathcal{E}$  and  $x$ .
- The statistician should see herself as a function **Ev**: a mapping from  $(\mathcal{E}, x)$  into a predefined set of **inferences about  $\theta$** .

$$(\mathcal{E}, x) \xrightarrow{\text{statistician, Ev}} \text{Inference about } \theta.$$

- For example, **Ev**( $\mathcal{E}, x$ ) might be:
  - ▶ the maximum likelihood estimator of  $\theta$
  - ▶ a 95% confidence interval for  $\theta$
- Birnbaum called  $\mathcal{E}$  the **experiment**,  $x$  the **outcome**, and **Ev** the **evidence**.

Note:

- 1 There can be **different** experiments with the same  $\theta$ .
- 2 Under some outcomes, we would agree that it is self-evident that these different experiments provide the **same evidence** about  $\theta$ .

### Example

Consider two experiments with the same  $\theta$ .

- 1  $X \sim \text{Bin}(n, \theta)$ , so we observe  $x$  successes in  $n$  trials.
- 2  $Y \sim \text{NBin}(r, \theta)$ , so we observe the  $r$ th success in the  $y$ th trial.

If we observe  $x = r$  and  $y = n$ , do we make the same inference about  $\theta$  in each case?

Consider two experiments  $\mathcal{E}_1 = \{\mathcal{X}_1, \Theta, f_{X_1}(x_1 | \theta)\}$  and  $\mathcal{E}_2 = \{\mathcal{X}_2, \Theta, f_{X_2}(x_2 | \theta)\}$ .

### Equivalence of evidence (Basu, 1975)

The equality or equivalence of  $\text{Ev}(\mathcal{E}_1, x_1)$  and  $\text{Ev}(\mathcal{E}_2, x_2)$  means that:

- 1  $\mathcal{E}_1$  and  $\mathcal{E}_2$  are related to the same parameter  $\theta$ .
- 2 Everything else being equal, the outcome  $x_1$  from  $\mathcal{E}_1$  warrants the same inference about  $\theta$  as does the outcomes  $x_2$  from  $\mathcal{E}_2$ .

- We now consider constructing statistical principles and demonstrate how these principles imply other principles.
- These principles all have the same form: under such and such conditions, the evidence about  $\theta$  should be the same.
- Thus they serve only to rule out inferences that satisfy the conditions but have different evidences. They do not tell us how to do an inference, only what to avoid.

# The principle of indifference

## Principle 1: Weak Indifference Principle, WIP

Let  $\mathcal{E} = \{\mathcal{X}, \Theta, f_{\mathcal{X}}(x | \theta)\}$ . If  $f_{\mathcal{X}}(x | \theta) = f_{\mathcal{X}}(x' | \theta)$  for all  $\theta \in \Theta$  then  $\text{Ev}(\mathcal{E}, x) = \text{Ev}(\mathcal{E}, x')$ .

- We are indifferent between two models of evidence if they differ only in the manner of the labelling of sample points.
- If  $X = (X_1, \dots, X_n)$  where the  $X_i$ s are a series of independent Bernoulli trials with parameter  $\theta$  then  $f_{\mathcal{X}}(x | \theta) = f_{\mathcal{X}}(x' | \theta)$  if  $x$  and  $x'$  contain the same number of successes.



## Principle 2: Distribution Principle, DP

If  $\mathcal{E} = \mathcal{E}'$ , then  $\text{Ev}(\mathcal{E}, x) = \text{Ev}(\mathcal{E}', x)$ .

- Informally, (Dawid, 1977), only aspects of an experiment which are relevant to inference are the sample space and the family of distributions over it.

## Principle 3: Transformation Principle, TP

Let  $\mathcal{E} = \{\mathcal{X}, \Theta, f_X(x | \theta)\}$ . For the bijective  $g : \mathcal{X} \rightarrow \mathcal{Y}$ , let  $\mathcal{E}^g = \{\mathcal{Y}, \Theta, f_Y(y | \theta)\}$ , the **same** experiment as  $\mathcal{E}$  but expressed in terms of  $Y = g(X)$ , rather than  $X$ . Then  $\text{Ev}(\mathcal{E}, x) = \text{Ev}(\mathcal{E}^g, g(x))$ .

- Inferences should not depend on the way in which the sample space is labelled, for example,  $X$  or  $X^{-1}$ .

## Theorem

$(DP \wedge TP) \rightarrow WIP.$

## Proof

Fix  $\mathcal{E}$ , and suppose that  $x, x' \in \mathcal{X}$  satisfy  $f_{\mathcal{X}}(x | \theta) = f_{\mathcal{X}}(x' | \theta)$  for all  $\theta \in \Theta$ , as in the condition of the WIP.

Let  $g : \mathcal{X} \rightarrow \mathcal{X}$  be the function which **switches**  $x$  for  $x'$ , but leaves all of the other elements of  $\mathcal{X}$  **unchanged**. Then  $\mathcal{E} = \mathcal{E}^g$  and

$$\begin{aligned} \text{Ev}(\mathcal{E}, x') &= \text{Ev}(\mathcal{E}^g, x') \quad [\text{by the DP}] \\ &= \text{Ev}(\mathcal{E}^g, g(x)) \\ &= \text{Ev}(\mathcal{E}, x), \quad [\text{by the TP}] \end{aligned}$$

which gives the WIP. □