

The Measurement of Statistical Evidence

Lecture 2 - part 2

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2021

What is randomness?

- recommended Sugita, H. (2018) Probability and Random Number, World Scientific, Chapter 2 a reasonably accessible treatment
- this issue was resolved in the 1960's by Chaitin, Kolmogorov and Solomonoff
- so what role does randomness have in probability and statistics?
- the concept of randomness is intimately connected with rigorizing what it means for a function f to be "computable" by a computer
- f is computable if there is a program to evaluate it and, since all inputs and outputs correspond to a finite binary sequences, we can restrict attention to the set \mathcal{F} of all functions $f : \mathbb{N}_0 \rightarrow \mathbb{N}_0$
- \mathcal{F} is uncountable (if countable, then can write $\{f_1, f_2, \dots\}$ and define f by $f(i) = 0$ if $f_i(i) \neq 0$ and $f(i) = 1$ if $f_i(i) = 0$) so $f \in \mathcal{F}$ but $f \neq f_i$ for any i)
- since every program (algorithm) corresponds to a finite binary sequence, and the set of all finite binary sequences is countable, this implies that the set \mathcal{F} of all computable functions (also called recursive functions) is countable

Kolmogorov Complexity (a sketch)

- put $\{0, 1\}^* =$ set of all finite sequences of 0's and 1's obtained from elements of \mathbb{N}_0 by binary expansion with highest order bit equal to 1, let the empty sequence correspond to $0 \in \mathbb{N}_0$, and consider \mathbb{N}_0 and $\{0, 1\}^*$ as identified
- so $0 \equiv ()$, $1 = 1 \cdot 2^0 \equiv (1)$, $2 = 0 \cdot 2^0 + 1 \cdot 2^1 \equiv (0, 1)$, $3 = 1 \cdot 2^0 + 1 \cdot 2^1 \equiv (1, 1)$, $4 = 0 \cdot 2^0 + 0 \cdot 2^1 + 1 \cdot 2^2 \equiv (0, 0, 1)$, etc.
- **note** - a *recursive function* (see reference for precise definition) on \mathbb{N}_0 is a function that can be constructed from some basic functions and an operation called minimization and a *partial function* (as opposed to a *total function*) f on \mathbb{N}_0 means that it may only be defined for some elements of \mathbb{N}_0
- let $l(x) = \text{length of } x \in \{0, 1\}^*$ (or $x \in \mathbb{N}_0$) and note for $x \in \mathbb{N}_0$, then $l(x) \leq \log_2 x + 1$ since $x = 2^{\log_2 x}$

Definition If $A : \{0, 1\}^* \rightarrow \{0, 1\}^*$ is a partial recursive function, when considered as a function $\mathbb{N}_0 \rightarrow \mathbb{N}_0$, then it is called an *algorithm*. The *computational complexity under algorithm A* of $x \in \{0, 1\}^*$ is defined by

$$K_A(x) = \min\{l(q) : q \in \{0, 1\}^*, A(q) = x\}$$

when $\{q \in \{0, 1\}^*, A(q) = x\} \neq \emptyset$ and $K_A(x) = \infty$ otherwise.

Theorem There exists algorithm A_0 such that for any algorithm A there is a constant $c_{A_0, A}$ s.t. $K_{A_0}(x) \leq K_A(x) + c_{A_0, A}$.

- such an A_0 is called a *universal algorithm* (not unique but the Theorem also applies to two universal algorithms and their absolute difference is bounded by a constant)

- so when $K_{A_0}(x)$ is big, say much bigger than $c_{A_0, A}$ and bigger than $K_A(x)$, then $(K_{A_0}(x) - K_A(x)) / K_{A_0}(x)$ is small

- for fixed A_0 , $K(x) = K_{A_0}(x)$ is called the *Kolmogorov complexity* of x

- if a different universal algorithm is used, the absolute difference in the Kolmogorov complexities is bounded by a fixed constant

Theorem

- (i) There exists constant $c > 0$ s.t. $K(x) \leq n + c$ for every $x \in (\{0, 1\}^n)^*$ and $n \in \mathbb{N}_0$. So $K : \{0, 1\}^* \rightarrow \mathbb{N}_0$ is a total function.
- (ii) If $n > c' > 0$ then

$$\#\{x \in (\{0, 1\}^n)^* : K(x) > n - c'\} > 2^n(1 - 2^{-c'}).$$

- $x \in (\{0, 1\}^n)^*$ is called *random* if $K(x) \approx n$
- this "complexity" measure of x is a measure of the randomness of the sequence, e.g. $(0, 1, 0, 1, 0, 1, \dots, 0, 1)$ is not random
- for large n , Theorem (ii) implies most elements of $(\{0, 1\}^n)^*$ are random

Example a computer program has computed 31.4 trillion decimal digits of π , or approximately $\log_2(10^{31.4 \times 10^{12}}) = 1.04 \times 10^{14}$ bits, and the program for this is considerably shorter so this approximation to π is not random

- so far, although most elements of $\{0, 1\}^*$ are random there is no known example of such a sequence

Theorem K is not a computable function (there is no program to compute it guaranteed to work).

- what this means is that there is no computable test for randomness
- implications for statistics: there is no test for randomness
- so what do current tests for randomness test? independent and identically distributed

Example *Champernowne's sequence*

- consider the following sequence

$(x_1, \dots, x_n) = (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 1, 0, 1, 1, 1, 2, 1, 3, 1, 4, \dots, \cdot)$ and subject this sequence to a test that the sequence is *i.i.d.* from a uniform distribution on $\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$

- if n is large enough the sequence will pass the test but it is not random
- recall, we stated earlier that the correct way to collect data was through *randomization* and, in particular, that this made the relative frequency distribution f_X suitable for assigning beliefs concerning the values taken by measurement X , namely, our belief that $X(\omega) \in A \subset \mathcal{X}$ is measured by

$$P(A) = \sum_{x \in A} f_X(x)$$

- why?
- my answer

Physical randomization corresponds to collecting the data in such a way that interested parties have absolutely no influence over the outcomes and, because of this, we can assert that the data is objective.

- there are physical systems, like coin tossing, drawing chips from a bowl, that we **believe**, when performed appropriately, cannot be controlled or manipulated and so we accept these as random systems and use them to randomize
- so randomness has nothing to do with probability, which measures belief, but it plays a key role in ensuring that the data is objective

Cox's Theorem

- R. Cox (1946) attempted to characterize probability via a set of simple axioms in the sense that, if we accept the axioms, then the correct way to measure beliefs is via a probability measure P , at least up to a 1-1 transformation of P
- the attractive aspect of this approach is that it did not involve utilities or relative frequencies rather it was more based on the logical properties we would want such a measure to have
- such a theorem was proved by Cox but a flaw in the proof was discovered in 1999
- this was fixed in 2009 but the modification is not very appealing
- so a general open problem in this area is to find a development similar to Cox's that is also simple and appealing
- see the text for more details and references