

# RANDOMNESS

Philosophy of Probability  
May 6th, 2013

## 1 FROM FINITE TO INFINITE FREQUENTISM

- Review
- Infinite Frequentism

## 1 FROM FINITE TO INFINITE FREQUENTISM

- Review
- Infinite Frequentism

## 2 RANDOMNESS

- Von Mises

## 1 FROM FINITE TO INFINITE FREQUENTISM

- Review
- Infinite Frequentism

## 2 RANDOMNESS

- Von Mises

## 3 COMPUTABILITY THEORY

## 1 FROM FINITE TO INFINITE FREQUENTISM

- Review
- Infinite Frequentism

## 2 RANDOMNESS

- Von Mises

## 3 COMPUTABILITY THEORY

## 4 DEFINITIONS OF RANDOMNESS

- Kolmogorov Complexity
- Betting and Martingales

## 1 FROM FINITE TO INFINITE FREQUENTISM

- Review
- Infinite Frequentism

## 2 RANDOMNESS

- Von Mises

## 3 COMPUTABILITY THEORY

## 4 DEFINITIONS OF RANDOMNESS

- Kolmogorov Complexity
- Betting and Martingales

## 5 EXTRAS

- Technical Snags

## Three Distinctions Among Finite Theories:

- Probability is a **measured** proportion vs. Probability is a proportion in a wider population, some units of which have been observed.

## Three Distinctions Among Finite Theories:

- Probability is a **measured** proportion vs. Probability is a proportion in a wider population, some units of which have been observed.
- Probability is an **actual** proportion vs. Probability is a **hypothetical** proportion



## Three Distinctions Among Finite Theories:

- Probability is a **measured** proportion vs. Probability is a proportion in a wider population, some units of which have been observed.
- Probability is an **actual** proportion vs. Probability is a **hypothetical** proportion
- Sample space (and algebra) generated by a **sequence** vs. Sample space is an arbitrary **unordered** set.

For reasons that may or may not have been well-motivated, many gave up on finite frequency theories, and turned to infinite ones.

Infinite frequentists cannot make the three distinctions we previously employed. Why?

- 1 In the cases in which human beings cannot perform infinitely many measurements (all cases?), an infinite frequency theory must define probability to be a proportion in some in a wider population, some units of which have not been observed.

- ② It's possible the universe contains finitely many objects (in total and/or of the type in which one is interested), in which case probability is a hypothetical (rather than actual) proportion.

# FORMALIZING INFINITE FREQUENTISM

If probability is a hypothetical proportion involving objects that we cannot measure, then questions about ascertainability arise: how can we ever discover or even approximate the probability of some event?

This is ironic because one of the chief virtues of finite frequentism was supposed to be that probabilities are easily learned via experiments.

- ③ Finally, it's not clear how to define proportions among unordered sets when infinitely many objects are under investigation). The symbol  $\frac{\infty}{\infty}$  does not denote a real number.
  - I.e., The only way of making a proportion precise is by taking the sample space to be generated by an ordered sequence.

How can we make infinite frequentism precise?



# FORMALIZING INFINITE FREQUENTISM

Rough idea: Take an infinite sequence of coin flips

$\langle T, H, T, T, T, H, T, H, H, T, \dots \rangle$

- Let  $E$  be any subset of the range of the sequence, e.g., “Heads” or  $\{H\}$ .
- After every finite number of flips, there is some proportion that have been heads. E.g., Above:
  - After 1 flip: 0
  - After 2 flips:  $\frac{1}{2}$ ,
  - After 3 flips  $\frac{1}{3}$ , Etc.

- In some sequences, these proportions approach a limiting value. Then one can define the probability of the set  $E$  to be this limiting proportion.

# FORMALIZING INFINITE FREQUENTISM

- In some sequences, these proportions approach a limiting value. Then one can define the probability of the set  $E$  to be this limiting proportion.
- There are one or two technical snags (see **Extras**), but this definition turns out to satisfy Kolmogorov's axioms.

# INFINITE FREQUENCIES

- The infinite sequences are intended to represent the outcome of repeating an experiment over and over again.

# INFINITE FREQUENCIES

- The infinite sequences are intended to represent the outcome of repeating an experiment over and over again.
- In order to attribute an event some **unique** probability, the relative frequency in the sequence must approach some **fixed** value.

# INFINITE FREQUENCIES

- Moreover, if a sequence exhibits patterns (e.g.  $\langle T, H, T, H, T, H \dots \rangle$ ) that are repeated indefinitely, then it seems wrong to interpret the sequence as an outcome of the **same** process.
  - Instead, one might assert the probability of an outcome depends upon **when** it occurs.

# INFINITE FREQUENCIES

- Moreover, if a sequence exhibits patterns (e.g.  $\langle T, H, T, H, T, H \dots \rangle$ ) that are repeated indefinitely, then it seems wrong to interpret the sequence as an outcome of the **same** process.
  - Instead, one might assert the probability of an outcome depends upon **when** it occurs.
- So philosophers, mathematicians, statisticians, and computer scientists became interested in characterizing **random** sequences, i.e., ones in which the probability of an event is fixed and constant across time.

What makes a sequence random?

Let's restrict our attention to **binary** sequences.



Von Mises' definition of randomness is vague, but the informal idea is clear:

If a sequence is random, then one should not be able to place bets on values of the sequence in a way that **guarantees** winning.

Here's an example to motivate the informal idea:

- Suppose the sequence is alternating heads and tails:  
 $\langle H, T, H, T, H, T \dots \rangle$

Here's an example to motivate the informal idea:

- Suppose the sequence is alternating heads and tails:  
 $\langle H, T, H, T, H, T \dots \rangle$
- Then one could detect the pattern and bet “Heads” on odd throws and “Tails” on even ones.

Here's an example to motivate the informal idea:

- Suppose the sequence is alternating heads and tails:  
 $\langle H, T, H, T, H, T \dots \rangle$
- Then one could detect the pattern and bet “Heads” on odd throws and “Tails” on even ones.
- Doing so would guarantee winning.

As soon as one starts asking for ways of making that precise, however, things get hairy ...

What counts as guaranteed winning?

- Suppose the coin lands heads  $\frac{1}{3}$  of the time in the limit.  
Recall, we are only considering randomness for sequences in which the event in question has a limiting frequency.

What counts as guaranteed winning?

- Suppose the coin lands heads  $\frac{1}{3}$  of the time in the limit. Recall, we are only considering randomness for sequences in which the event in question has a limiting frequency.
- If you use the observed frequency to estimate the limiting frequency, then you'll eventually know the coin is biased towards tails.

What counts as guaranteed winning?

- Suppose the coin lands heads  $\frac{1}{3}$  of the time in the limit. Recall, we are only considering randomness for sequences in which the event in question has a limiting frequency.
- If you use the observed frequency to estimate the limiting frequency, then you'll eventually know the coin is biased towards tails.
- On each throw, bet \$1 on tails.



What counts as guaranteed winning?

- You win  $\frac{2}{3}$  of the time, and so you win \$2 for every dollar that you lose.

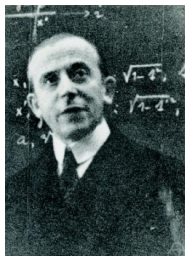
What counts as guaranteed winning?

- You win  $\frac{2}{3}$  of the time, and so you win \$2 for every dollar that you lose.
- So if you start with a big enough bank account to support your bets, then as the game goes on, you win an arbitrarily large amount of money for sure.

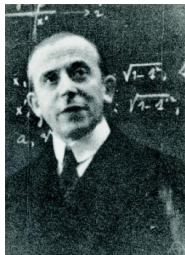
What counts as guaranteed winning?

- You win  $\frac{2}{3}$  of the time, and so you win \$2 for every dollar that you lose.
- So if you start with a big enough bank account to support your bets, then as the game goes on, you win an arbitrarily large amount of money for sure.
- This argument only fails for events with probability (exactly) one half; there, your expected earnings are zero.

**Revision:** There is no betting rule that is guaranteed to win **particular** bets.



- Informal idea: One can guarantee winning on particular bets if one can identify **subsequences** that are exclusively ones or exclusively zeroes.



- So Von Mises defines what he calls a “Kollektiv”, which is a sequence in which one cannot pick subsequences that are exclusively ones or zeros without already knowing the values of the sequence.

One (very bad) attempt to formalize this idea is as follows:

- **Definition:** A sequence is **random** if every infinite subsequence has the same (limiting) proportion of zeroes as the whole sequence.

One (very bad) attempt to formalize this idea is as follows:

- **Definition:** A sequence is **random** if every infinite subsequence has the same (limiting) proportion of zeroes as the whole sequence.
- **Problem:**
  - Suppose the limiting proportion of zeroes is between 0 and 1.



One (very bad) attempt to formalize this idea is as follows:

- **Definition:** A sequence is **random** if every infinite subsequence has the same (limiting) proportion of zeroes as the whole sequence.
- **Problem:**
  - Suppose the limiting proportion of zeroes is between 0 and 1.
  - Then the sequence has infinitely many zeroes and infinitely many ones.

One (very bad) attempt to formalize this idea is as follows:

- **Definition:** A sequence is **random** if every infinite subsequence has the same (limiting) proportion of zeroes as the whole sequence.
- **Problem:**
  - Suppose the limiting proportion of zeroes is between 0 and 1.
  - Then the sequence has infinitely many zeroes and infinitely many ones.
  - So there are some infinite subsequences with only zeroes, and some with only ones.

This objection is really unfair to Von Mises, but it was a standard reason for dismissing discussions of randomness.

## Today:

- We'll discuss several mathematically precise definitions of randomness that have become accepted since Von Mises work.
- We'll also discuss the argument that they capture Von Mises intuitive ideas about randomness.

## What we should discuss but won't:

- “Failed” definitions of randomness (e.g., Church's) and why they were dismissed (e.g., Ville's objection)
- Why do we need a theory of random sequences anyway?

**Hilbert's Problems:** In 1900, David Hilbert outlined 23 open problems in mathematics and physics at his address at the International Congress of Mathematicians in Paris.



**Hilbert's 10th Problem:** Find an “algorithm” that generates integer solutions to Diophantine Equations, if any exist. For example:

$$x^2 + y^2 = z^2$$

$$ax + by = c$$

$$x^2 - ny^2 = 1$$

$$x^3 + y^3 = z^3$$

are all Diophantine equations.



**Entscheidungsproblem:** Find an “algorithm” that determines whether any given formula of first- order logic is valid. For example:

$$(\forall x)(P(x) \vee \neg P(x))$$

vs.

$$(\exists x)(P(x) \wedge \neg Q(x))$$



- The concept of an “algorithm” was not made precise in either of Hilbert’s challenges.



- The concept of an “algorithm” was not made precise in either of Hilbert’s challenges.
- **Philosophical Problem:** Find a precise notion of “algorithm” that characterizes what we mean by a “mechanical” step-by-step process.

- The concept of an “algorithm” was not made precise in either of Hilbert’s challenges.
- **Philosophical Problem:** Find a precise notion of “algorithm” that characterizes what we mean by a “mechanical” step-by-step process.
- **Mathematical Problem:** Show there are (or are not) algorithms, in the precisely defined sense, meeting Hilbert’s challenges.

- In the early 20th century, logicians developed several definitions of “mechanical” or “effectively” or “algorithmically” computable.
- They also gave several circular arguments that certain formal definitions capture the intuitive concept of an “algorithm” [Sieg, 2009]

- In the early 20th century, logicians developed several definitions of “mechanical” or “effectively” or “algorithmically” computable.
- They also gave several circular arguments that certain formal definitions capture the intuitive concept of an “algorithm” [Sieg, 2009]
- Turing [1936] gives a rather ingenious argument . . .

# TURING'S ARGUMENT

Following [Sieg, 2008]'s reconstruction, Turing argues that humanly-executable algorithms on symbols satisfy two types of constraints.



## Boundedness:

- Capable of immediately differentiating only finitely many symbols
- Capable of immediately using only finite amounts of memory



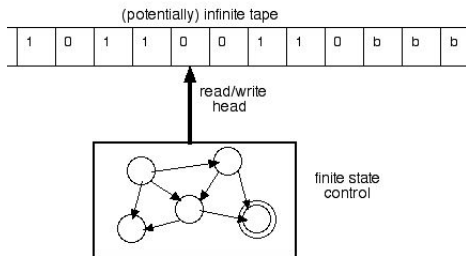
## Locality:

- Only elements of observed symbols can be changed
- Which symbols are observed can be changed, but each of the new observed symbols must be within a bounded distance  $L$  of a previously observed square.



# TURING MACHINES

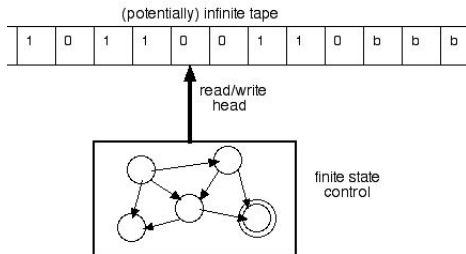
## Turing Machine



Turing then introduces a model of a computing device, now called a **Turing Machine**.

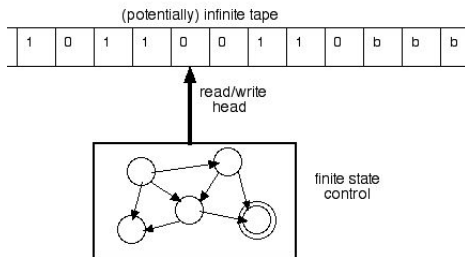


## Turing Machine



- Turing gives an informal argument that his machines satisfy the boundedness and locality conditions, **and**
- He argues that all devices satisfying the conditions are Turing machines.

## Turing Machine



**Church Turing Thesis:** The set of “algorithmically” computable functions are equal to those that can be executed on Turing machines.

Sieg [1994] formalizes the boundedness and locality axioms and proves the set of functions satisfying them are precisely the Turing machine computable functions.

What does all of this have to do with probability and randomness?

# TWO ASPECTS OF RANDOMNESS

Here are two intuitive features of “random” sequences:

- They exhibit no **pattern**.
- They cannot be **predicted**.

How can we make the notion of a “pattern” precise?

Consider the following two sequences:

Sequence 1: 001001001001001001001001001001

Sequence 2: 110010100011111100110010011100

Consider the following two sequences:

Sequence 1: 001001001001001001001001001001

Sequence 2: 110010100011111100110010011100

- The first one can be described succinctly: its 001 repeated ten times.



Consider the following two sequences:

Sequence 1: 001001001001001001001001001001

Sequence 2: 110010100011111100110010011100

- The first one can be described succinctly: its 001 repeated ten times.
- Describing the second is harder . . .

- How can we capture the notion of a simple “description” of a sequence of symbols?

- How can we capture the notion of a simple “description” of a sequence of symbols?
- **Key Idea:** Identify a description with the length of a Turing machine program, as Turing machines represent the symbolic manipulations that agents with limited computational abilities (like us) can perform.

Suppose you had to write a computer program to print the two strings:

```
001001001001001001001001001001
```

```
110010100011111100110010011100
```

Suppose you had to write a computer program to print the two strings:

```
001001001001001001001001001001
```

```
110010100011111100110010011100
```

- **Program 1:** Print 001 repeated ten times.

Suppose you had to write a computer program to print the two strings:

```
001001001001001001001001001001
```

```
110010100011111100110010011100
```

- **Program 1:** Print 001 repeated ten times.
- **Program 2:** Print 110010100011111100110010011100.

Suppose you had to write a computer program to print the two strings:

```
001001001001001001001001001001
```

```
110010100011111100110010011100
```

- **Program 1:** Print 001 repeated ten times.
- **Program 2:** Print 110010100011111100110010011100.

The second program is as long as the string itself!

- Strings with patterns can be **compressed**: they can be “encoded” in a short computer program that prints them.



- Strings with patterns can be **compressed**: they can be “encoded” in a short computer program that prints them.
- Conversely, strings that can be compressed must exhibit some sort of pattern.

- Strings with patterns can be **compressed**: they can be “encoded” in a short computer program that prints them.
- Conversely, strings that can be compressed must exhibit some sort of pattern.
- Ergo, random strings are incompressible ones, i.e., ones for which there is no short program.

A little more formally ...

- The **Kolmogorov Complexity**  $K(s)$  of a string  $s$  is the length of the shortest Turing machine program that prints  $s$ .
  - I'm omitting one technical part of this definition that won't concern us now.

A little more formally ...

- The **Kolmogorov Complexity**  $K(s)$  of a string  $s$  is the length of the shortest Turing machine program that prints  $s$ .
  - I'm omitting one technical part of this definition that won't concern us now.
- Let  $n$  be some whole number. A string  $s$  is called  **$n$ -incompressible** if  $K(s) \geq l(s) - n$ , where  $l(s)$  is the length of  $s$ .

Kolmogorov complexity is defined for strings that are **finitely** long.  
How can it be extended to the infinite sequences?

- **Definition 1:** An infinite sequence  $s$  is **random** if there is some constant  $n$  such that all of the initial segments of  $s$  are  $n$ -incompressible.

What about formalizing the notion of **prediction**?

- The exact mathematical ideas are rather hard. Here's the brief overview. For details, see Durrett [2010]



- The exact mathematical ideas are rather hard. Here's the brief overview. For details, see Durrett [2010]
- In the late 1930s, the French mathematicians Lévy and Ville introduced what are called **martingales**.

- The exact mathematical ideas are rather hard. Here's the brief overview. For details, see Durrett [2010]
- In the late 1930s, the French mathematicians Lévy and Ville introduced what are called **martingales**.
- For our purposes, think of a martingale is a particular way to place bets - say on the flips of a coin.

- The exact mathematical ideas are rather hard. Here's the brief overview. For details, see Durrett [2010]
- In the late 1930s, the French mathematicians Lévy and Ville introduced what are called **martingales**.
- For our purposes, think of a martingale is a particular way to place bets - say on the flips of a coin.
- A martingale has the property of being **fair**:
  - If you place your bets according to a martingale, then your expected earnings at stage  $n + 1$  are equal to your earnings at stage  $n$ . So if you start with no earnings, then your expected earnings on any stage are exactly 0.

- Some martingales are not Turing computable.

- Some martingales are not Turing computable.
- Since we are interested in what can be predicted by computationally bounded agents like ourselves, we should confine ourselves to **computable** martingales.

- Some martingales are not Turing computable.
- Since we are interested in what can be predicted by computationally bounded agents like ourselves, we should confine ourselves to **computable** martingales.
- The definition of a computable martingale is a bit different but satisfies a similar “fairness” condition.

- Some martingales are not Turing computable.
- Since we are interested in what can be predicted by computationally bounded agents like ourselves, we should confine ourselves to **computable** martingales.
- The definition of a computable martingale is a bit different but satisfies a similar “fairness” condition.
- **Definition 2:** A sequence is **random** if there is no computable martingale that earns money while betting on it.

## THEOREM (SCHNORR [1971])

*The two definitions of randomness are equivalent.*

In fact, both are equivalent to a third notion called **Martin-Löf** randomness, which is supposed to formalize the idea that sequences exhibiting patterns for infinitely long are **rare**.



## Morals:

- There are several precise mathematical notions of randomness.

## Morals:

- There are several precise mathematical notions of randomness.
- Several definitions are equivalent, and each captures some intuitive features about our judgments of randomness.

## Morals:

- There are several precise mathematical notions of randomness.
- Several definitions are equivalent, and each captures some intuitive features about our judgments of randomness.
- Finally, some of the most useful theorems from probability theory (laws of large numbers, law of iterated logarithm, Borel Cantelli Lemma, Hoeffding's inequality etc.) hold for such random sequences.
  - Note: I'm not sure whether the central limit theorem has been proven for such random sequences.

But what's the philosophical upshot for philosophy of probability?

To be honest, I'm not completely sure.

How do they fair with respect to Salmon's criteria for adequacy?

- **Admissibility:** As Suppes argues, the infinite frequency interpretation does satisfy Kolmogorov's axioms, plus countable additivity.

How do they fair with respect to Salmon's criteria for adequacy?

- **Admissibility:** As Suppes argues, the infinite frequency interpretation does satisfy Kolmogorov's axioms, plus countable additivity.
- **Applicability:** As I said, some of the most useful theorems from probability theory hold for such random sequences. But one might still have questions:
  - Do data observed in scientific practice have high Kolmogorov complexity? If not, then are such data readily dismissed as not random?

**Ascertainability:** One might think that because probabilities are defined as relative frequencies in the infinite limit, that there's no finite time by which we can be sure of an event's probability.

This is a standard philosophical worry [Hájek, 2009], but I'm not sure it's true.

## Ascertainability:

- In certain cases in which we know a lot about the process, results like Hoeffding's inequality can make it "probable" that our estimates of probability are close.
  - Formally, the measure of random sequences deviating from the limiting proportion decreases exponentially as a function of sample size.



## Ascertainability:

- In certain cases in which we know a lot about the process, results like Hoeffding's inequality can make it “probable” that our estimates of probability are close.
  - Formally, the measure of random sequences deviating from the limiting proportion decreases exponentially as a function of sample size.
  - Whether such measure ought to (can be?) interpreted as a probability itself is open for grabs.

## Ascertainability:

- In certain cases in which we know a lot about the process, results like Hoeffding's inequality can make it "probable" that our estimates of probability are close.
  - Formally, the measure of random sequences deviating from the limiting proportion decreases exponentially as a function of sample size.
  - Whether such measure ought to (can be?) interpreted as a probability itself is open for grabs.
- If we don't know a lot about the process, then our estimates may be really far off. But I am not sure this is a consequence of the infinite frequency interpretation of probability theory; it may just be an artifact of the mathematics of probability theory.

## Ascertainability:

- In certain cases in which we know a lot about the process, results like Hoeffding's inequality can make it "probable" that our estimates of probability are close.
  - Formally, the measure of random sequences deviating from the limiting proportion decreases exponentially as a function of sample size.
  - Whether such measure ought to (can be?) interpreted as a probability itself is open for grabs.
- If we don't know a lot about the process, then our estimates may be really far off. But I am not sure this is a consequence of the infinite frequency interpretation of probability theory; it may just be an artifact of the mathematics of probability theory.
- If you want a final paper topic that mixes technical questions with philosophical ones, there's plenty to study in this area.

# REFERENCES I

- Durrett, R. (2010). *Probability: Theory and Examples*. Cambridge University Press.
- Hájek, A. (2009). Fifteen arguments against hypothetical frequentism. *Erkenntnis*, 70(2):211235.
- Schnorr, C.-P. (1971). A unified approach to the definition of random sequences. *Mathematical Systems Theory*, 5(3):246258.
- Sieg, W. (1994). Mechanical procedures and mathematical experience. *Mathematics and mind*, page 71117.
- Sieg, W. (2008). Church without dogma: Axioms for computability. In *New computational paradigms*, page 139152. Springer.
- Sieg, W. (2009). On computability. In Irvine, A., editor, *Handbook of the Philosophy of Mathematics*, pages 535—630.
- Suppes, P. (2002). *Representation and Invariance of Scientific Structures*. CSLI Publications Stanford.
- Turing, A. M. (1936). On computable numbers, with an application to the entscheidungsproblem. *Proceedings of the London mathematical society*, 42(2):230265.

Let  $s$  be an finite sequence and  $E$  be any subset of the range of  $s$ .

- **Technical snag:** The set of all  $E$  with limiting frequencies (i.e., probabilities) may not form an algebra because it is not closed under union Suppes [2002].
- But if the number of sequence elements in a set  $E$  has a limiting value, then there is some algebra (namely,  $\{\emptyset, E, E^c, \Omega\}$ ) over which one can define a probability measure. It's not clear how useful such a definition is.