

# Towards prediction via randomness

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Algorithmic randomness is highly related with probability theory, statistics, dynamical system and other many areas.

- Recent development of randomness enables us to apply.
- Some researchers come to think that we need to know what randomness means.

In this talk we discuss the following.

- What is algorithmic randomness?
- Some recent development and my contribution.
- My research plan to a prediction theory.

# *The topics in AIT*

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Algorithmic Information Theory is the result of putting Shannon's information theory and Turing's computability theory into a cocktail shaker and shaking vigorously. (G. J. Chaitin)

AC Algorithmic "Kolmogorov" Complexity

AP Algorithmic "Solomonoff" Probability

(→ prediction or machine learning)

US Universal "Levin" Search

AR Algorithmic "Martin-Löf" Randomness

(→ probability theory or statistical test)

# From frequency to regularity

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Casting a dice → Probability is just frequency.

The sunrise problem → Frequency is not appropriate.

- Even if you know the sun has risen for  $n$  days, we believe it more than  $\frac{n}{n+1}$ .
- If the sun did not rise today, the belief of the sunrise tomorrow would be much less than  $\frac{n}{n+1}$ .

Is there an appropriate initial distribution for Bayes rule?

# Solomonoff's induction

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**Theorem 1** (Solomonoff '64). *There is an optimal prediction  $\mathcal{M}$ .*

- The space is  $\Sigma^\omega$ .
- Optimal in c.e. and up to a multiplicative constant
- Highly related with Kolmogorov complexity
- A good compression means a good prediction.

# What does randomness mean?

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Intuitively TFAE:

- Not random
- Has regularity
- Compressible
- Predictable

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- ❖ Computability
- ❖ Martingales in randomness
- ❖ Universal martingale
- ❖ Optimal martingale

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# Randomness by martingale



# Three approaches

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Many notions of randomness has been proposed. Martin-Löf Randomness has been regarded as the most natural one.

Randomness has (at least) three approaches.

- Typicality by a test concept (Martin-Löf 1966)
- Unpredictability by martingales (Schnorr 1971)
- Uncompressibility by Kolmogorov complexity (Levin, Schnorr 1973)

Most notions of randomness also have similar characterizations.

# Computability

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A set  $A \subseteq \mathbb{N}$  is *computable* iff  $1_A : \mathbb{N} \rightarrow \{0, 1\}$  is computable.

A set  $A$  is *c.e.* iff  $A = \text{dom}(f)$  for a partial computable function.

A real  $r \in [0, 1]$  is *computable* iff its binary expansion is computable.

A real  $r$  is *c.e.* iff  $\{q \in \mathbb{Q} : q < r\}$  is c.e.

There exist a c.e. set and a c.e. real that are not computable.

$2^\omega$ : Cantor space of infinite binary sequences

$\mu$ : generated from  $\mu([\sigma]) = 2^{-|\sigma|}$

We often identify  $2^\omega$  with  $[0, 1]$ .

# Martingales in randomness

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**Definition 2.** A function  $d : 2^* \rightarrow \mathbb{R}^+ \cup \{0\}$  is a martingale if

$$d(\sigma) = \frac{d(\sigma 0) + d(\sigma 1)}{2}.$$

The  $d$  is a supermartingale if we replace  $=$  by  $\geq$ .

**Proposition 3.** TFAE:

- $A \in 2^\omega$  is ML-random.
- $\sup_n d(A \upharpoonright n) < \infty$  for each c.e. martingale.
- $\sup_n d(A \upharpoonright n) < \infty$  for each c.e. supermartingale.

The set of ML-random sequences has measure 1.

# Universal martingale

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**Definition 4.** *The success set of  $d$  is*

$$S[d] = \{A : d(A) = \sup_n d(A \upharpoonright n) = \infty\}.$$

*A c.e. (super)martingale  $d$  is universal if*

$$S[d] \supseteq S[f]$$

*for each c.e. (super)martingale  $f$ .*

**Proposition 5.** *There exists a universal c.e. (super)martingale.*

# Optimal martingale

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**Definition 6.** A c.e. (super)martingale  $d$  is optimal if for each c.e. (super)martingale  $f$  there exists  $c$  s.t.

$$f(\sigma) \leq c \cdot d(\sigma)$$

for all  $\sigma$ .

**Proposition 7.** No c.e. martingale is optimal.  
There exists an optimal c.e. supermartingale.

*Remark 8.* This optimal c.e. supermartingale is nothing but an optimal prediction.

Note that it is optimal up to a multiplicative constant.  
There are (at least) two constructions: by a direct enumeration and by complexity.

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Randomness by  
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**General randomness**

- ❖ Computable  
topological space
- ❖ Computability
- ❖ Computability of  
measures
- ❖ Measure  
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- ❖ Computably  
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- ❖ Optimality?

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# General randomness

# Computable topological space

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❖ Computability of measures

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**Definition 9** (Hertling and Weihrauch 2009). A computable topological space or CTS is a 4-tuple  $\mathbf{X} = (X, \tau, \beta, \nu)$  such that

- $(X, \tau)$  is a topological  $T_0$ -space,
- $\nu : \subseteq \Sigma^* \rightarrow \beta$  is a notation of a base  $\beta$  of  $\tau$ ,
- $\text{dom}(\nu)$  is recursive and
- $\nu(u) \cap \nu(v) = \bigcup \{ \nu(w) : (u, v, w) \in S \}$  for all  $u, v \in \text{dom}(\nu)$  for some r.e. set  $S \subseteq (\text{dom}(\nu))^3$ .

# Computability

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Define a representation  $\delta : \subseteq \Sigma^\omega \rightarrow X$  of the points as

$$x = \delta(p) \iff (\forall w \in \Sigma^*)(w \ll p \iff x \in \nu(w)).$$

A point is  $\delta$ -computable if it has a computable  $\delta$ -representation.

Computability of sets and functions are similarly defined.



# Computability of measures

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$M(X)$ : the space of bounded non-negative Borel measures

**Proposition 10.**  $G$ : the finite union of base sets  
A countable subbase of the  $A$ -topology  $\tau_A$ :

$$\{\mu : \mu(G) > q\}, \{\mu : \mu(X) < q\}$$

**Theorem 11.**  $(M(X), \tau_A, \beta_A, \nu_A)$  is a CTS.

**Definition 12.** A measure is computable if it is a  
computable point in the CTS.

# Measure randomness

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Let  $(X, \mathcal{A}, \mu)$  be a measure space.

A *filtration* is a sequence of sub- $\sigma$ -algebra  $(\mathcal{A}_n)$  such that

$\mathcal{A}_n \subseteq \mathcal{A}_{n+1}$  for each  $n$ .

A sequence of  $\mathcal{A}$ -measurable functions  $(f_n, \mathcal{A}_n)$  is called a *supermartingale* if  $\int f_n d\mu < \infty$  and  $\int_A f_n d\mu \geq \int_A f_{n+1} d\mu$  for all  $A \in \mathcal{A}_n$ .

**Theorem 13.** A point  $x$  is measure  $\mu$ -random iff  $\sup_n f_n(x) < \infty$  for each  $(\nu_{\mathbb{N}}, \delta, \bar{\rho}_{<})$ -computable supermartingale  $(f_n, \mathcal{A}_n)$

# Computationally Regular

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**Definition 14** (regular). *A non-negative measure  $\mu$  is regular if  $\forall A \in \mathcal{A}$  and  $\forall \epsilon > 0$ , there exists a closed set  $F_\epsilon$  s.t.  $F_\epsilon \subset A$ ,  $A \setminus F_\epsilon \in \mathcal{A}$  and  $\mu(A \setminus F_\epsilon) < \epsilon$ .*

**Definition 15** (computationally regular). *A non-negative measure  $\mu$  is computably regular if for all  $u$  there exists  $v_n$  and  $p_n$  uniformly in  $u$  and  $n$  s.t.*

- $\mu(\bigcup_n \nu(v_n)) \rightarrow \mu(\nu(u))$ ,
- $\nu(v_n) \subseteq \psi^-(p_n) \subseteq \nu(u)$ ,
- $\mu(\psi^-(p_n) \setminus \nu(v_n)) \leq 2^{-n}$ .

**Proposition 16.** *If the measure is computably regular, there exists a universal  $(\nu_{\mathbb{N}}, \delta, \bar{\rho}_{<})$ -comp. martingale.*

# Optimality?

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**Question 17.** *Does there exist an optimal  $(\nu_{\mathbb{N}}, \delta, \bar{\rho}_{<})$ -computable supermartingale?*

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- ❖ SLLN for randomness
- ❖ Hartman-Wintner LIL for randomness
- ❖ Convergence speed
- ❖ Effective Birkhoff's ergodic theorem

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# Application

# SLLN for randomness

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**Theorem 18.** Let  $\mu_1$  be a continuous computable measure on  $\mathbb{R}$  such that  $m = \int |z| d\mu_1 < \infty$  is computable. Let  $\mu = \prod \mu_1$  be the products of infinite same measures. Then

$$\{y_i\} \text{ is } \mu\text{-random} \Rightarrow \frac{\sum_{i=1}^n y_i}{n} \rightarrow \int x d\mu.$$

**Theorem 19.** Let  $\mu_1$  be a continuous computable measure on  $\mathbb{R}$  such that  $m = \int |z| d\mu_1 = \infty$ . Let  $\mu = \prod \mu_1$  be the products of infinite same measures. Then

$$\{y_i\} \text{ is } \mu\text{-random} \Rightarrow \limsup_n \frac{|\sum_{i=1}^n y_i|}{n} = \infty.$$

# Hartman-Wintner LIL for randomness

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**Theorem 20** (Hartman-Wintner LIL). *Let  $\mu = \prod \mu_1$  be a computable measure on  $\mathbb{R}^{\mathbb{N}}$  such that  $\mu_1$  is continuous,  $\int z \mu(dz) = 0$  and  $\int z^2 \mu(dz) = \sigma^2$  is computable. Then*

$$\{x_i\} \text{ is } \mu\text{-random} \Rightarrow \limsup_n \frac{\sum x_i}{\sqrt{2n \ln \ln n}} = \sigma.$$

# Convergence speed

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❖ Hartman-Wintner  
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Let  $K^c = \{A : (\forall n)K(A \upharpoonright n) > n - c\}$ .

**Theorem 21** (Davie '01). *There exists a computable function  $n(c, \epsilon)$  s.t. if  $A \in K^c$  then for all  $n > n(c, \epsilon)$ ,*

$$\left| \frac{S_n(A)}{n} - \frac{1}{2} \right| < \epsilon.$$

*For  $c$  and  $\lambda > 1$ , there exists a computable function  $n(c, \lambda)$  s.t. if  $A \in K^c$  then for all  $n > n(c, \lambda)$ ,*

$$S_n(A) \leq \frac{n}{2} + \lambda \sqrt{\frac{n}{2} \log \log n}.$$



# Effective Birkhoff's ergodic theorem

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- ❖ Hartman-Wintner LIL for randomness
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**Definition 22.**  $T$  is  $\ln^2$ -ergodic if  $\forall f, g$

$$\gamma_n(f, g) = \left| \frac{1}{n} \sum_{i < n} \int f \circ T^i \cdot g d\mu - \int f d\mu \int g d\mu \right| \leq \frac{c_{f,g}}{(\ln(n))^2}$$

**Theorem 23** (Birkhoff's ergodic theorem for random points; V'yugin '97, Nandakumar '08, Hoyrup and Rojas '09).

$(X, \mu)$ : a CPS

$T : X \rightarrow X$  an effectively measurable measure-preserving map

$f \in L^1(X, \mu)$  an effectively measurable function

$T$ :  $\ln^2$ -ergodic

Then  $\exists n(c, \epsilon)$  comp. function s.t.

if  $x \in K_c$  then for all  $n > n(c, \epsilon)$ ,

$$\left| \frac{1}{n} \sum_{i < n} \int f \circ T^i \cdot g d\mu - \int f d\mu \int g d\mu \right| < \epsilon$$

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**Probability and  
prediction**

- ❖ What is probability?
- ❖ Optimal prediction
- ❖ Radon-Nikodym operator
- ❖ Game-theoretic probability
- ❖ End

# Probability and prediction

# What is probability?

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Three main interpretations of probability:

- Frequency probability → von Mises
- Subjective probability → some researchers
- Propensity probability → Kolmogorov

# Optimal prediction

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❖ End

$X$ : a computable topological space with computable regularity

**Question 24.** *Does there exist an optimal  $(\nu_{\mathbb{N}}, \delta, \bar{\rho}_{<})$ -computable supermartingale on  $X^{\mathbb{N}}$ ?*

There are (at least) two approaches:

- Define monotone complexity  $Km$  on a general space.
- Enumerate all such supermartingales.

The latter approach is more simple.

# Radon-Nikodym operator

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However there are some difficulties.

**Theorem 25** (Weihrauch). *Radon-Nikodym operator on  $[0, 1]$  is not computable.*

Then how about using the setting of game-theoretic probability?

# Game-theoretic probability

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**Parameters:** Measurable space  $(X, \mathcal{F})$ ,  $K_0 \in \mathbb{R}$

**Players:** Forecaster, Skeptic, Reality

**Protocol:**

FOR  $n = 1, 2, \dots$ :

Forecaster announces  $p_n$  on  $(\Omega, \mathcal{F})$ .

Skeptic announces  $f_n$  on  $\Omega$

Reality announces  $x_n \in \Omega$ .

$$K_n := K_{n-1} + f_n(x_n) - \int_{\Omega} f_n dp_n.$$

Effectivized game-theoretic probability is essentially the same as generalized randomness.

# End

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Thank you!