

# Allender's conjecture and its impacts on meta-complexity

Shuichi Hirahara

National Institute of Informatics, Japan

# CiE 2012 (Computability in Europe)

Curiouser and Curiouser: The Link  
between Incompressibility and Complexity

➤ Eric's invited paper at CiE 2012

Eric Allender

*Conjecture 1.*  $\text{NEXP} = \text{NP}^R$ .

*Conjecture 2.* BPP is the class of problems non-adaptively polynomial-time reducible to  $R$ .

More specifically, let  $R$  denote the set of Kolmogorov-random strings. Let BPP denote the class of problems that can be solved with negligible error by probabilistic polynomial-time computations, and let NEXP denote the class of problems solvable in nondeterministic exponential time.

*Conjecture 1.*  $\text{NEXP} = \text{NP}^R$ .

*Conjecture 2.* BPP is the class of problems non-adaptively polynomial-time reducible to  $R$ .

These conjectures are not only audacious; they are obviously false!  $R$  is not a decidable set, and thus it is absurd to suggest that the class of problems reducible to it constitutes a complexity class.

The absurdity fades if, for example, we interpret “ $\text{NP}^R$ ” to be “the class of problems that are NP-Turing reducible to  $R$ , no matter which universal machine we use in defining Kolmogorov complexity”. The lecture will survey the body of work (some of it quite recent) that suggests that, when interpreted properly, the conjectures may actually be true.

➤ My first paper was about this conjecture.  
(MFCS 2014, joint work with Akitoshi Kawamura)

➤ Today: Recent progress and its impacts

# “Randomness” in Complexity and **Computability**

## ➤ Complexity Theory

BPP := {The class of problems solvable efficiently with **randomness**}.

Example: Polynomial Identity Testing  $\in$  BPP



**Try to understand BPP through the lens of computability!**

## ➤ Computability Theory

$R_{KU}$  := {The set of **Kolmogorov-random** strings } is not computable.

Example: 0000000000  $\notin R_{KU}$ , 10110100111  $\in R_{KU}$ .

# Kolmogorov complexity

- The *Kolmogorov complexity*  $K_U(x)$  of a finite string  $x$  is the “shortest program” size to print  $x$ .

## Examples

- $00000000000000000000000000000000$  ( $= 0^n$ ) can be compressed into a program “print ‘0’  $\times n$ ”.

$$K_U(0^n) = \log n + O(1).$$

- $r := 10101101100110101000101010$  chosen uniformly and randomly.

$$K_U(r) \approx |r| \text{ with high probability.}$$

# Formal Definition and Universality

- We need to fix an “interpreter”  $U$ .

**Definition:** Kolmogorov complexity

The *Kolmogorov complexity* of a finite string  $x \in \{0,1\}^*$  with respect to a Turing machine  $U$  is defined as

$$K_U(x) := \min\{ |d| : U \text{ outputs } x \text{ on input } d \}.$$

- $U$  can be chosen so that  $K_U$  is smallest up to an additive  $O(1)$  term.

**Definition:** Universality of  $U$

A machine  $U$  is said to be *universal* if for any  $M$  and any  $x$ ,

$$K_U(x) \leq K_M(x) + O(1).$$

# Kolmogorov-Randomness

- Kolmogorov complexity gives rise to the notion of **randomness**.

## Definition: Kolmogorov-Randomness

- A string  $x$  is said to be **Kolmogorov-random** if  $K_U(x) \geq |x|$ .
- Define  $R_{K_U} := \{ x \mid K_U(x) \geq |x| \}$ .

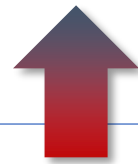
## Examples

- 00000000000000000000000000000000  $\notin R_{K_U}$  : not random
- 10101101100110101000101010  $\in R_{K_U}$  : random

# Complexity vs. Computability Theory

## ➤ Complexity Theory

$BPP := \{\text{The class of problems solvable efficiently with randomness}\}.$



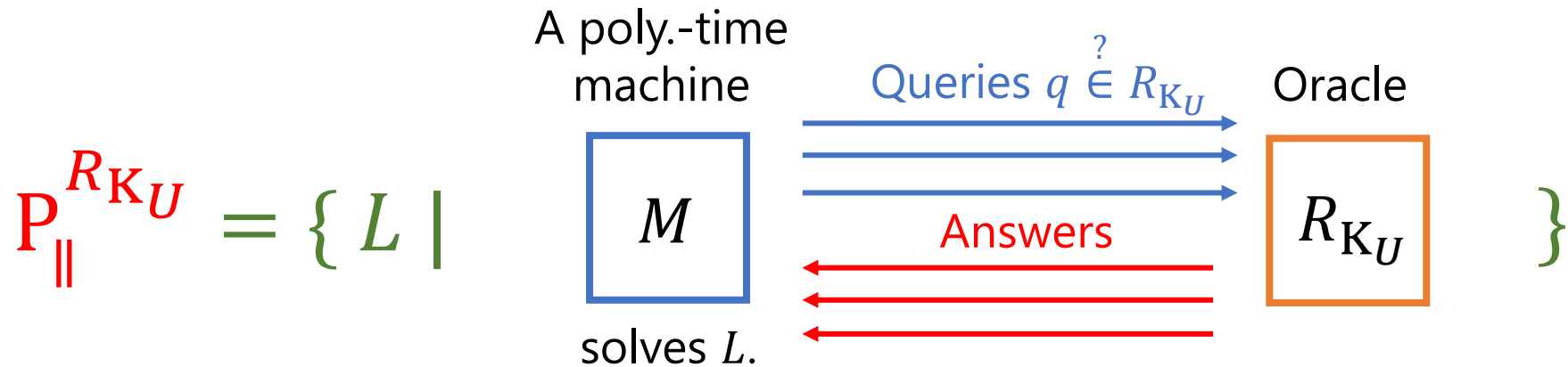
**Bridge the gap via an efficient reduction to  $R_{KU}$ .**

## ➤ Computability Theory

$R_{KU} := \{\text{The set of Kolmogorov-random strings}\}$  is **not computable**.

# Reductions to Kolmogorov-random strings

- What can be solved efficiently by nonadaptively asking whether  $q \in R_{K_U}$  or not? (no matter what  $U$  is)



[Buhrman, Fortnow, Koucký & Loff (2010)]

$$\text{BPP} \subseteq P_{\parallel}^{R_{K_U}} \subseteq \text{PSPACE}$$

[Allender, Friedman & Gasarch (2013)]



$$\text{BPP} \subseteq \bigcap_{U \text{ universal}} P_{\parallel}^{R_{KU}} \subseteq \text{PSPACE}$$

Allender's Conjecture (2012)

$$\text{BPP} = \bigcap_{U} P_{\parallel}^{R_{KU}} .$$

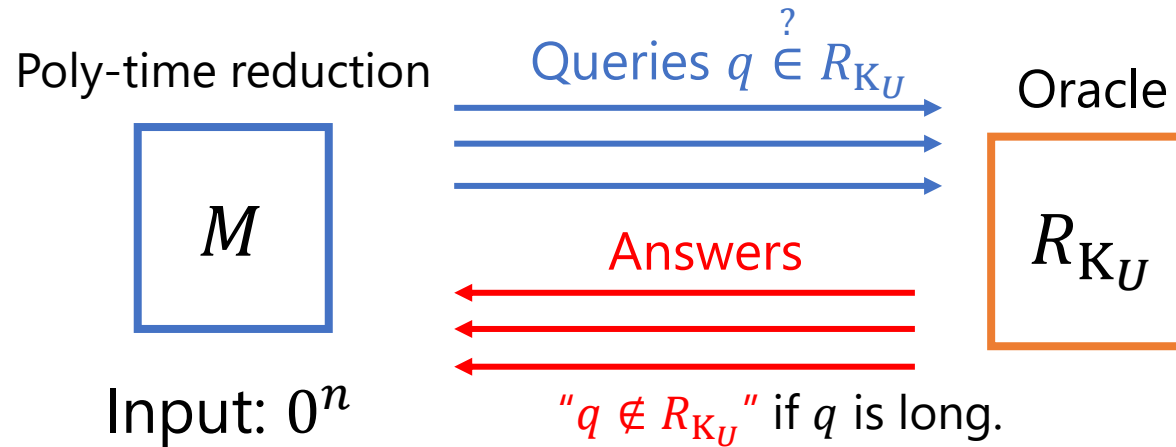
Motivation:

- $\text{MCSP}^{\text{HALT}} \approx R_{KU}$ . [Allender, Buhrman, Koucky, van Melkebeek, Ronneburger'06]  
(Minimum HALT-Oracle Circuit Size Problem)
- An approach towards the  $P = \text{BPP}$  conjecture?

$$\bigcap_{U} P_{\text{dtt}}^{R_{KU}} = P \quad [\text{Allender, Buhrman, Koucky 2006}]$$

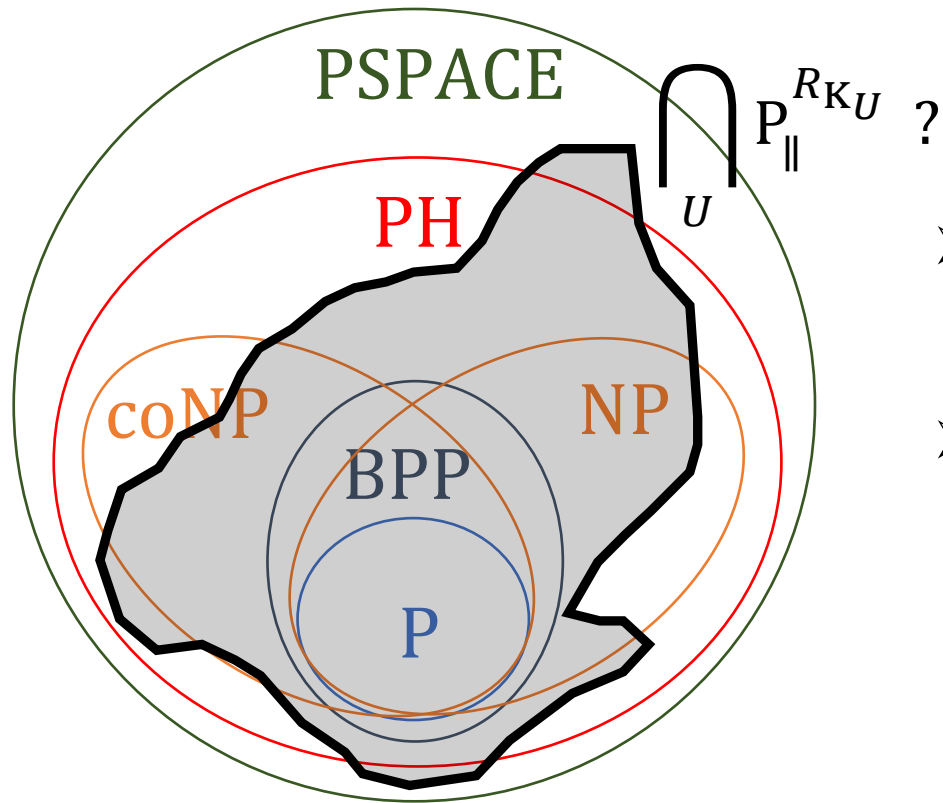
(dtt: disjunctive truth table reductions)

# The Intuition behind Allender's Conjecture



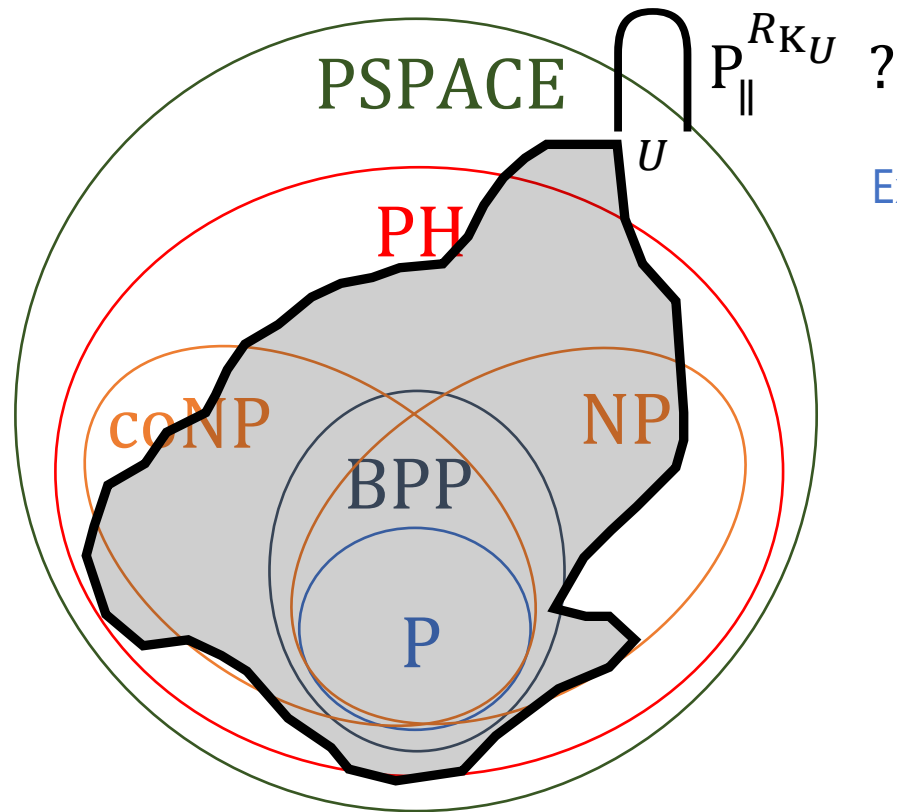
- $K_U(q) = O(\log n)$  for any query  $q$ .
- If  $|q| > O(\log n)$ , then  $q \notin R_{K_U}$  (i.e. the answer is "No").
- On input  $0^n$ , a polynomial-time nonadaptive reduction **cannot** make use of **any query** of length  $> O(\log n)$ .

# Complexity Classes

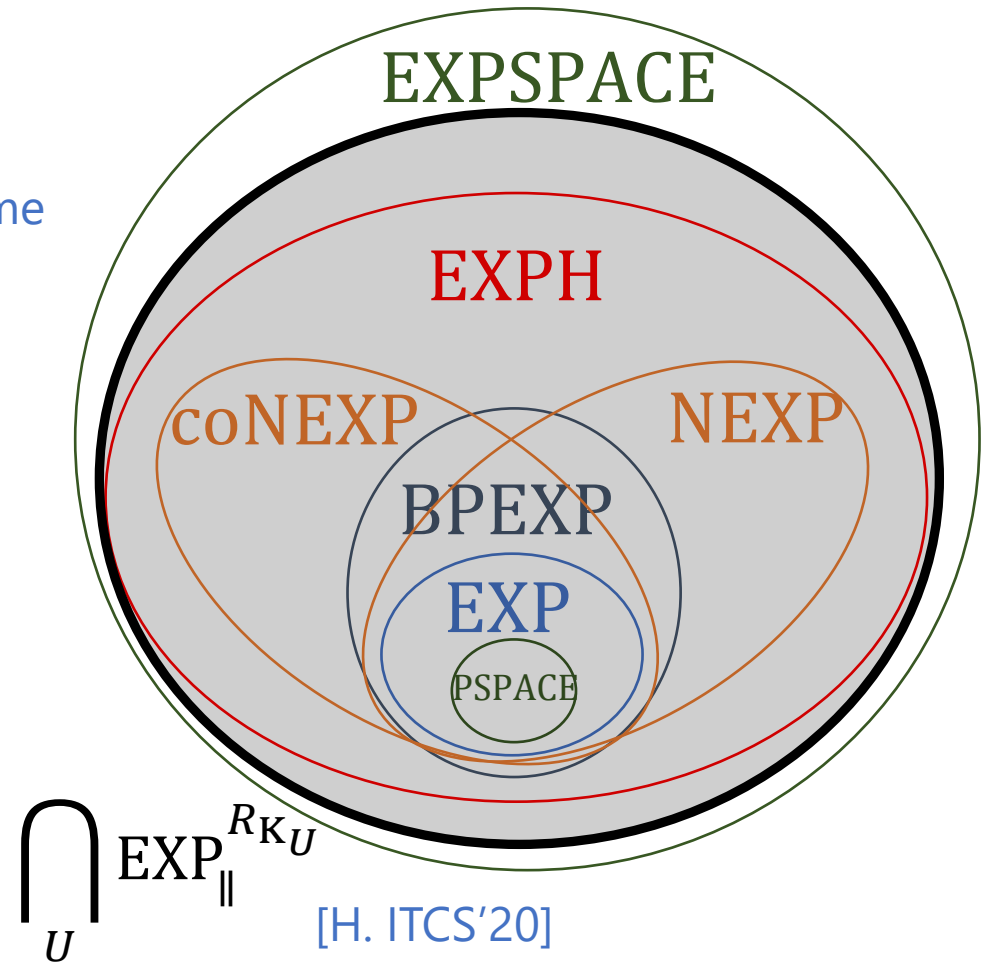
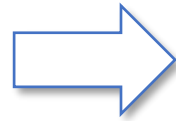


- Let us focus on input  $0^n$ .
- This is essentially equivalent to considering an **exponential-time analogue**.

# Exponential-Time Classes



Exponential-time analogues



# Allender's conjecture is false (unless EXPH collapses)

## Theorem [H. ITCS'20]

For every universal Turing machine  $U$ ,

$$\text{EXPH} \subseteq \text{EXP}_{\parallel}^{R_{K_U}}.$$



A padding argument

## Corollary

Allender's conjecture is false (i.e.,  $\text{BPP} \neq \bigcap_U \text{P}_{\parallel}^{R_{K_U}}$ )  
unless  $\text{EXPH} \subseteq \text{BPEXP}$ .

# Other conjectures

[Allender, Buhrman, Koucký, van Melkebeek, and Ronneburger (2006)]

- $\text{PSPACE} \subseteq \bigcap_U \text{P}^{R_{K_U}} \subseteq \text{EXPSPACE}.$

[Allender, Friedman, Gasarch (2013)]

- $\text{NEXP} \subseteq \bigcap_U \text{NP}^{R_{K_U}} \subseteq \text{EXPSPACE}.$

[Allender, Buhrman, Koucký (2006)]

**Hypothesis** [Allender, Buhrman, Koucký (2006)]

$$\text{PSPACE} = \bigcap_U \text{P}^{R_{K_U}} .$$

**Conjecture** [Allender (2012)]

$$\text{NEXP} = \bigcap_U \text{NP}^{R_{K_U}} .$$

# Unexpected Power of Random Strings

**Main Theorem** [H. STOC'20]

$$\text{EXP}^{\text{NP}} \subseteq \text{P}^{R_{\text{K}_U}}$$

- It follows that  $\text{PSPACE} \neq \bigcap_U \text{P}^{R_{\text{K}_U}}$  and  $\text{NEXP} \neq \bigcap_U \text{NP}^{R_{\text{K}_U}}$  unless  $\text{EXP}^{\text{NP}} \subseteq \text{NEXP}$ .

$$\text{EXP}^{\text{NP}} \subseteq \bigcap_U \text{P}^{R_{\text{K}_U}} \subseteq \text{EXPSPACE}$$

# NP-hardness of $K_U$ under nonadaptive reductions

## Theorem [H. STOC'20]

For every universal Turing machine  $U$ ,

$$\text{NP} \subseteq \text{quasiP}_{\parallel}^{K_U}.$$

The oracle returns  $K_U(q)$  on query  $q$ .

➤ The proof is inspired by [H. ITCS'20].

➤ Proof Idea:

- Symmetry of information

$$K(y | x) + K(x) \approx K(x, y) \approx K(x | y) + K(y).$$

- $k$ -wise direct product generator  $\text{DP}_k$



# $k$ -Wise Direct Product Generator [H. STOC'20]

$$\text{DP}_k: \{0,1\}^n \times (\{0,1\}^\lambda)^k \rightarrow \{0,1\}^{\lambda k+k}$$

$$\text{DP}_k(x; z_1, \dots, z_k) = (z_1, \dots, z_k, \text{Enc}(x)_{z_1}, \dots, \text{Enc}(x)_{z_k})$$

A pseudorandom generator construction based on a "hard" truth table  $x$  that extends seed  $z$  by  $k$  bits.

- $\text{Enc}: \{0,1\}^n \rightarrow \{0,1\}^{2^\lambda}$ , a list-decodable error-correcting code
- We may choose  $\text{Enc}$  so that  $\lambda = O(\log n)$ .

## A Reconstruction Property of $\text{DP}_k$ :

For every oracle  $D: \{0,1\}^{\lambda k+k} \rightarrow \{0,1\}$  and every  $x \in \{0,1\}^n$ , if

$$\Pr_{z \sim \{0,1\}^{nk}} [D(\mathbf{DP}_k(x; z)) = 1] - \Pr_{w \sim \{0,1\}^{nk+k}} [D(w) = 1] \geq \frac{1}{2},$$

then  $K^{\text{poly}(n), D}(x) \leq O(\lambda k)$ .

$\exists$  a poly-time program  $M^D$  of length  $O(\lambda k)$  that prints  $x$ .

# Claim: $\text{NP} \subseteq \text{quasiP}_{\parallel}^{\text{K}}$

➤ Let  $L \in \text{NP}$  and  $V$  be a verifier for  $L$ .

➤ Let  $x \in \{0,1\}^n$  be an input.

$$(V(x, y_x) = 1.)$$

➤ Let  $y_x \in \{0,1\}^{\text{poly}(n)}$  be the lexicographically first certificate (if  $x \in L$ ).

➤ **Goal:** To distinguish  $\text{DP}_k(y_x; -)$  from the uniform distribution.

$$\begin{aligned} \bullet \quad \text{K}(x, \text{DP}_k(y_x; z)) &\leq \text{K}(x) + |z| + O(\log k) && \because \text{K}(y_x|x) = O(1) \\ &\leq \text{K}(x) + k\lambda + O(\log k). && \lambda = O(\log n) \end{aligned}$$

$$\begin{aligned} \bullet \quad \text{K}(x, w) &\geq \text{K}(x) + \text{K}(w|x) - O(\log n) && \because \text{Symmetry of Information} \\ &\geq \text{K}(x) + k\lambda + k - O(\log n) && \because \text{K}(w|x) \approx |w| \text{ with high probability} \end{aligned}$$

➤  $\text{K}$  can distinguish  $\text{DP}_k(y_x; -)$  for a sufficiently large  $k := O(\log n)$ .

# Claim: $\text{NP} \subseteq \text{quasiP}_{\parallel}^{\text{K}}$ (continued)

➤ Define  $D_x(w) := 1$  iff  $K(x, w) \leq \mathbf{s}$ .

$$\bullet \Pr_z[D_x(\text{DP}_k(y_x; z)) = 1] = 1. \quad \bullet \Pr_w[D_x(w) = 1] \leq \frac{1}{2}.$$

$$\Rightarrow K^{\text{poly}(n), D_x}(y_x) \leq O(k\lambda) = O(\log^2 n). \quad \text{: The reconstruction property}$$

➤ **Goal:** To distinguish  $\text{DP}_k(y_x; -)$  from the uniform distribution.

$$\begin{aligned} \bullet K(x, \text{DP}_k(y_x; z)) &\leq K(x) + |z| + O(\log k) && \text{: } K(y_x|x) = O(1) \\ &\leq K(x) + k\lambda + O(\log k) \text{ := } \mathbf{s}. && \lambda = O(\log n) \end{aligned}$$

$$\begin{aligned} \bullet K(x, w) &\geq K(x) + K(w|x) - O(\log n) && \text{: Symmetry of Information} \\ &\geq K(x) + k\lambda + k - O(\log n) && \text{: } K(w|x) \approx |w| \text{ with high probability} \end{aligned}$$

➤  $K$  can distinguish  $\text{DP}_k(y_x; -)$  for a sufficiently large  $k := O(\log n)$ .

# Claim: $\text{NP} \subseteq \text{quasiP}_{\parallel}^{\text{K}}$ (continued)

➤ Define  $D_x(w) := 1$  iff  $\text{K}(x, w) \leq s$ .

$$\bullet \Pr_z[D_x(\text{DP}_k(y_x; z)) = 1] = 1. \quad \bullet \Pr_w[D_x(w) = 1] \leq \frac{1}{2}.$$

$$\Rightarrow \text{K}^{\text{poly}(n), D_x}(y_x) \leq O(k\lambda) = O(\log^2 n).$$

➤ Given  $x$ , enumerate all poly-time programs  $d$  of size  $O(\log^2 n)$  and check if

$U^{D_x}(d)$  is a certificate for  $x \in L$ .



## Remark

➤ If  $x = 0^n$ , we obtain  $\text{NP} \cap \text{Tally} \subseteq \text{quasiP}_{\parallel}^{R_{\text{KU}}}$ . [H. ITCS'20]

➤ If  $x \sim \{0,1\}^n$ , we obtain  $\text{NP} \times \{\mathcal{U}\} \subseteq \text{Heur quasiP}_{\parallel}^{R_{\text{KU}}}$ .

∴ the threshold  $s \approx |x| + |w|$  if  $x \sim \{0,1\}^n$

# Two mysteries of complexity theory

1. What is the (errorless) **average-case complexity** of PH? [Levin'86]

e.g.,  $\text{DistPH} \not\subseteq \text{AvgP}$ ? (Is PH hard on average?)



**Main Theorem [H. FOCS'20]:** The equivalence of these two questions

2. What is the **complexity** of computing time-bounded Kolmogorov complexity?  
= **meta-complexity** [Ko'91]

e.g.,  $\text{GapMINKT}^{\text{PH}} \not\subseteq \text{P}$ ? (Is it hard to approximate PH-oracle Kolmogorov complexity?)

# Main Theorem

- An interdisciplinary link between **average-case complexity** and **worst-case meta-complexity**

## Main Theorem [H. FOCS'20]

(Average-case hardness of PH)

(Worst-case hardness of meta-complexity)

$\text{DistPH} \not\subseteq \text{AvgP}$

$\iff$

$\text{GapMINKT}^{\text{PH}} \notin \text{P}$

### Significance:

#### Average-Case Complexity

- It provides new proof techniques of analyzing **average-case complexity** via **meta-complexity**.

#### Meta-Complexity

- It classifies the complexity of  $\text{GapMINKT}^{\text{PH}}$  as a "DistPH-complete" problem.

Application: a hardness amplification theorem for PH

# Meta-Complexity – Complexity of Complexity

➤ Examples of meta-computational problems: MCSP, MKTP, MINKT, ...

MINKT [Ko'91] = "Compute the time-bounded Kolmogorov complexity"

- $t$ -time-bounded Kolmogorov complexity of  $x$

$K^t(x) :=$  (the length of a shortest program that prints  $x$  in  $t$  steps)

- $\text{MINKT} = \{(x, 1^t, 1^s) \mid K^t(x) \leq s\}$ .

# Meta-Complexity – Complexity of Complexity

➤ Examples of meta-computational problems: MCSP, MKTP, MINKT, ...

$\text{MINKT}^A$  [Ko'91] = "Compute the  $A$ -oracle time-bounded Kolmogorov complexity"

- $A$ -oracle  $t$ -time-bounded Kolmogorov complexity of  $x$

$K^{t,A}(x) :=$  (the length of a shortest program  $M^A$  that prints  $x$  in  $t$  steps)

- $\text{MINKT}^A = \{(x, 1^t, 1^s) \mid K^{t,A}(x) \leq s\}$ .

Remark: In general, we may have  $A \not\leq_m^p \text{MINKT}^A$ .

It is easy to see  $\text{MINKT}^A \in \text{NP}^A$ .



# Average-Case Complexity = Meta-Complexity

**Theorem** [H. (FOCS'20)]

$$\text{DistPH} \subseteq \text{AvgP} \iff \text{GapMINKT}^{\text{PH}} \in \text{P}$$

For every  $A \in \text{PH}$ ,  
 $\text{GapMINKT}^A \in \text{P}$

- $\text{GapMINKT}^A$ : an  $O(\log n)$ -additive approximation version of  $\text{MINKT}^A$ .
- **Corollary:** A new technique of analyzing **average-case complexity** by **meta-complexity**.

Average-Case Complexity

$$\text{DistPH} \subseteq \text{Avg}_{0.99}\text{P}$$

**Corollary**  
 average-case hardness  
 amplification for PH



$$\text{DistPH} \subseteq \text{AvgP}$$

[H. FOCS'18, CCC'20]



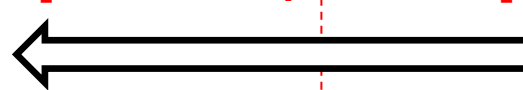
Worst-Case Meta-Complexity

$$\text{Gap}(K^{\text{PH}} \text{ vs } K) \in \text{P}$$



$$\text{GapMINKT}^{\text{PH}} \in \text{P}$$

[H. ITCS'20, STOC'20]



# Claim: $\text{GapMINKT}^{\text{NP}} \in \text{P} \implies \text{DistNP} \subseteq \text{AvgP}$

- Let  $L \in \text{NP}$  and  $V$  be a verifier for  $L$ .
- Let  $x \sim \{0,1\}^n$  be a **random** input.  $(V(x, y_x) = 1.)$
- Let  $y_x \in \{0,1\}^{\text{poly}(n)}$  be the lexicographically first certificate (if  $x \in L$ ).
- **Goal:** To distinguish  $\text{DP}_k(y_x; -)$  from the uniform distribution.
  - $\text{K}^{2t, \text{SAT}}(x, \text{DP}_k(y_x; z)) \leq \text{K}^{t, \text{SAT}}(x) + |z| + O(\log k) \quad \because \text{K}^{t, \text{SAT}}(y_x|x) = O(1)$   
 $\leq n + k\lambda + O(\log k). \quad \lambda = O(\log n)$
  - $\text{K}^{2t, \text{SAT}}(x, w) \geq \text{K}(x, w) \geq |x| + |w| - O(1) \quad \text{with high probability over } x, w \sim \{0,1\}^*$   
 $\geq n + k\lambda + k - O(\log n) \quad \because \text{K}(w|x) \approx |w| \text{ with high probability}$
- $\text{K}^{2t, \text{SAT}}$  can distinguish  $\text{DP}_k(y_x; -)$  for a sufficiently large  $k := O(\log n)$ .

# Claim: $\text{GapMINKT}^{\text{NP}} \in \text{P} \implies \text{DistNP} \subseteq \text{AvgP}$

➤ Define  $D_x(w) := 1$  iff  $K^{2t, \text{SAT}}(x, w) \leq n + k\lambda + O(\log k)$ .

$$\bullet \Pr_z[D_x(\text{DP}_k(y_x; z)) = 1] = 1. \quad \bullet \Pr_w[D_x(w) = 1] \leq \frac{1}{2}.$$

$$\implies K^{\text{poly}(n), D_x}(y_x) \leq k + O(\log n) \quad \theta(k\lambda) = \theta(\log^2 n).$$

Can be improved using complexity-theoretic PRG.

➤ Given  $x$ , enumerate all poly-time programs  $d$  of size  $O(\log n)$  and check if

$$U^{D_x}(d) \text{ is a certificate for } x \in L.$$

$\implies$  a **heuristic polynomial-time** algorithm for  $L \in \text{NP}$ . ■

# New Worst- to Average-Case Connections

## Main Theorems [H. STOC'21]

$$(1) \text{UP} \not\subseteq \text{DTIME}(2^{O(n/\log n)}) \implies \text{DistNP} \not\subseteq \text{AvgP}$$

A strong variant  
of Heuristica  
doesn't exist!

$$\text{PH} \not\subseteq \text{DTIME}(2^{O(n/\log n)}) \implies \text{DistPH} \not\subseteq \text{AvgP}$$

$$(3) \text{NP} \not\subseteq \text{DTIME}(2^{O(n/\log n)}) \implies \text{DistNP} \not\subseteq \text{Avg}_{\text{P}}\text{P}$$

P-computable  
average-case  
polynomial-time

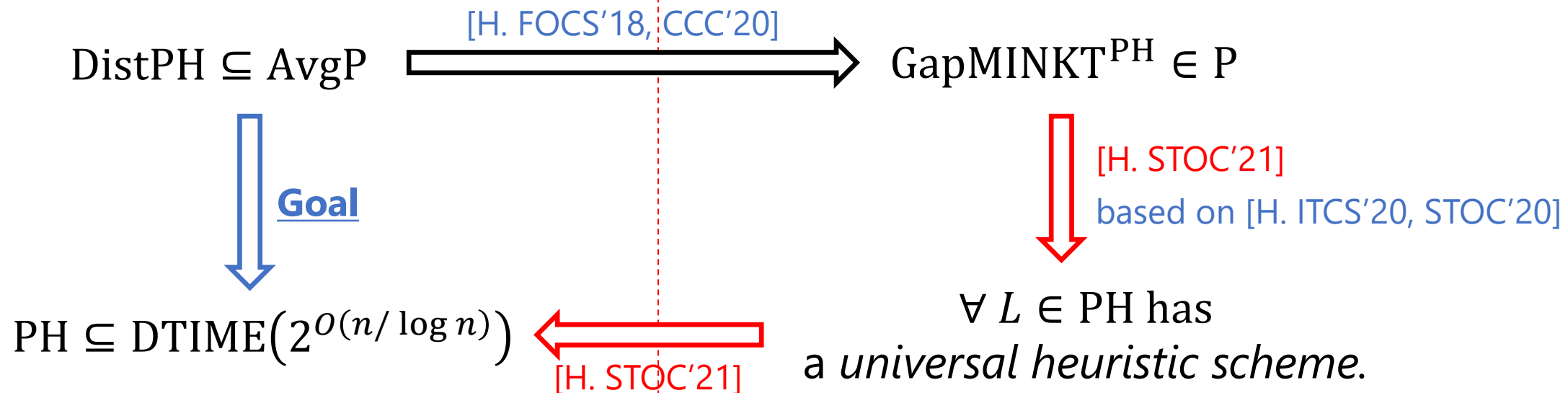
- $n$  denotes the length of inputs (encoded as binary strings).
- $\text{Avg}_{\text{P}}\text{P} (\subseteq \text{AvgP})$ : the class of  $(L, \mathcal{D})$  solvable by average-case polynomial-time algorithms whose running time can be "estimated."

**Theorem** [H. STOC'21]

$$(2) \text{ PH } \not\subseteq \text{DTIME}(2^{O(n/\log n)}) \Rightarrow \text{DistPH} \not\subseteq \text{AvgP}$$

Average-Case Complexity

Worst-Case Meta-Complexity



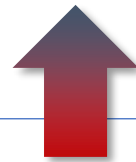
➤ See my survey in EATCS Bulletin for the proof!

# Complexity vs. Computability Theory

## ➤ Complexity Theory

~~BPP := {The class of problems solvable efficiently with randomness}.~~

NISZK := { The class of problems that have  
non interactive statistical zero knowlege }.



**Bridge the gap via an efficient reduction to  $R_{KU}$ .**

## ➤ Computability Theory

$R_{KU}$  := {The set of Kolmogorov-random strings} is **not computable**.

# Kolmogorov complexity characterizes NISZK

**Theorem** [Allender-H.-Tirumala (ITCS'23)]

Approximation  
of  $R_K$

$$\text{NISZK} = \{ A: \text{decidable} \mid A \leq_m^{\text{BPP}} \widetilde{R}_K \}$$

$$\text{NISZK}_L = \{ A: \text{decidable} \mid A \leq_m^{\text{RNC}^0} \widetilde{R}_K \}$$

## Open Question

- Can this new characterization give a new insight into NISZK?

# In Conclusion

- I am very influenced by Eric's work.
- Thank you for fundamental contributions to meta-complexity!