Kolmogorov Complexity

Fangzhou Zhai

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- A. N. Kolmogorov.
- Kolmogorov Complexity
- Kolmogorov Complexity and Data Compression

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A. N. Kolmogorov

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Universal Turing Machine

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A universal Turing Machine \mathcal{U} is a computing device that can execute unambiguous instructions (or program, or input) p, and possibly yields an output string $\mathcal{U}(p)$.

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The Notion of Information

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$$H(X) := \mathbb{E}[log \frac{1}{p(x)}]$$

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Example

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Example

- Y = 100101011101001001000101010010111101010

X carries as much information as "42 1s" while there is no immediate short description of Y.

Kolmogorov Complexity I

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A description wraps all the information of a string. The minimal description length of a string is thus a measurement of its complexity, or the information it carries.

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Definition (Kolmogorov Complexity)

The Kolmogorov Complexity of $x \in \{0,1\}^*$ is defined as

$$K(x) := \min_{p:\mathcal{U}(p)=x} l(p)$$

where l(p) denotes the length of program p.

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Kolmogorov complexity is also referred to as "absolute information" in comparison with entropy.

Kolmogorov Complexity II

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- Any initial segment of an algebraic number has low Kolmogorov complexity. e.g., first million digits of the greatest root of x² = 2.
- The Kolmogorov Complexity of a string that consists of n ones is at most $\log n + c$.
- Losslessly compressed data can be seen as a description.

Kolmogorov Complexity III

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Kolmogorov Complexity III



Kolmogorov Complexity III



This 2.36*MB* fractal picture is generated by one complex polynomial. The description length of this picture is not much larger than that of the polynomial.

Upper Bound

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Theorem

There exists a constant c such that for all $x \in \{0, 1\}^*$,

$K(x) \leq l(x) + c$

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Proof.

Consider program "print string x".

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Theorem (Lower Bound)

 $|\{x|K(x) < k\}| < 2^k$

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Proof.

There are only $2^k - 1$ descriptions of length less than k.

For each n, at least one string of length n is of Kolmogorov Complexity at least n.

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Definition (Random String)

x is random if $K(x) \ge l(x)$.

The probability that a uniformly random binary string has low Kolmogorov complexity is fairly small:

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Theorem

Let $X_i \sim iid B(\frac{1}{2})$, then

$$P[K(X^n) < n-k] < 2^{-k}$$

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This is really a tiny fragment: for files of size 100kB, only 2^{-8192} of them can be possibly compressed by 1kB, and $2^{-409600}$ of them can be possibly compressed to half its original size. Compression softwares are, nevertheless, running happily, because the files we use them to compress, luckily, belongs to this tiny fragment.



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- By far the majority of the strings have their Kolmogorov complexity close to their length, thus cannot be compressed much. Compression is possible in practice because our files lie in the tiny bit that is compressible.

Further Readings

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 Kolmogorov Complexity and Entropy. http://homepages.cwi.nl/~paulv/papers/info.pdf

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- Worship Andrey N. Kolmogorov. http://www.kolmogorov.com/. http://theor.jinr.ru/~kuzemsky/ankolmogbio.html.

Thanks for your attention.