

# A Small Theorem for small $\mathbf{m}$

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## Abstract

If a semi measure is greater than the universal semi-measure  $\mathbf{m}$  up to a multiplicative constant, then it is exotic in that it has infinite mutual information with the halting sequence.

## 1 Introduction

In this note, we show that semi measures that majorize the algorithmic probability have infinite mutual information with the halting sequence. For a probability  $p$  over  $\{0, 1\}^*$ ,  $[p] \subset \{0, 1\}^\infty$  is the set of infinite sequences  $\beta \in [p]$  such that  $U_x(\beta)$  outputs the bit representation of  $p(x)$ . The algorithm  $U$  is a standard universal Turing machine.  $\mathbf{K}(x|y)$  is the prefix Kolmogorov complexity.  $\mathbf{m}$  is the algorithmic probability.  $\mathbf{I}(x : y) = \mathbf{K}(x) + \mathbf{K}(y) - \mathbf{K}(x, y)$  is the mutual information between two strings. For infinite sequences  $\alpha, \beta \in \{0, 1\}^\infty$ ,  $\mathbf{I}(\alpha : \beta) = \log \sum_{x, y \in \{0, 1\}^*} \mathbf{m}(x|\alpha) \mathbf{m}(y|\beta) 2^{\mathbf{I}(x:y)}$  [Lev74]. The halting sequence is  $\mathcal{H}$ . The amount of mutual information between a probability  $p$  and  $\mathcal{H}$  is  $\mathbf{I}(p : \mathcal{H}) = \inf_{\beta \in [p]} \mathbf{I}(\beta : \mathcal{H})$ .

**Theorem.** *If  $\mathbf{w}$  is a semimeasure on  $\{0, 1\}^*$  and  $\mathbf{m} < O(1)\mathbf{w}$  then  $\mathbf{I}(\mathbf{w} : \mathcal{H}) = \infty$ .*

The amount of information that  $\mathcal{H}$  has about  $x \in \{0, 1\}^*$  is  $\mathbf{I}(x; \mathcal{H}) = \mathbf{K}(x) - \mathbf{K}(x|\mathcal{H})$ . For positive real functions  $f$ , by  $<^+ f$ ,  $>^+ f$ ,  $=^+ f$ , and  $<^{\log} f$ ,  $>^{\log} f$ ,  $\sim f$  we denote  $\leq f + O(1)$ ,  $\geq f - O(1)$ ,  $= f \pm O(1)$  and  $\leq f + O(\log(f+1))$ ,  $\geq f - O(\log(f+1))$ ,  $= f \pm O(\log(f+1))$ . Furthermore,  $<^* f$ ,  $>^* f$  denotes  $< O(1)f$  and  $> f/O(1)$ . The term  $\stackrel{*}{=} f$  is used to denote  $>^* f$  and  $<^* f$ . The chain rule states  $\mathbf{K}(x) + \mathbf{K}(y|x, \mathbf{K}(x)) =^+ \mathbf{K}(x, y)$ .

## 2 Kolmogorov Complexity is Exotic

We cover material on busy beaver functions. Let  $\Omega = \sum \{2^{-\|p\|} : U(p) \text{ halts}\}$  be Chaitin's Omega,  $\Omega_n \in \mathbb{Q}_{\geq 0}$  be the rational formed from the first  $n$  bits of  $\Omega$ , and  $\Omega^t = \sum \{2^{-\|p\|} : U(p) \text{ halts in time } t\}$ . For  $n \in \mathbb{N}$ , let  $\mathbf{bb}(n) = \min\{t : \Omega_n < \Omega^t\}$ .  $\mathbf{bb}^{-1}(m) = \arg \min_n \{\mathbf{bb}(n-1) < m \leq \mathbf{bb}(n)\}$ . Let  $\Omega[n] \in \{0, 1\}^*$  be the first  $n$  bits of  $\Omega$ . For  $t \in \mathbb{N}$  define the function  $\mathbf{m}^t(x) = \sum \{2^{-\|p\|} : U(p) = x \text{ in } t \text{ steps}\}$  and for  $n \in \mathbb{N}$ , we have  $\mathbf{m}_n(x) = \sum \{2^{-\|p\|} : U(p) = x \text{ in } \mathbf{bb}(n) \text{ steps}\}$ .

**Lemma 1** *For  $n = \mathbf{bb}^{-1}(m)$ ,  $\mathbf{K}(\Omega[n]|m, n) = O(1)$ .*

**Proof.** For a string  $x$ , let  $BB(x) = \inf\{t : \Omega^t > 0.x\}$ . Enumerate strings of length  $n$ , starting with  $0^n$ , and return the first string  $x$  such that  $BB(x) \geq m$ . This string  $x$  is equal to  $\Omega[n]$ , otherwise let  $y$  be the largest common prefix of  $x$  and  $\Omega[n]$ . Thus  $BB(y) = \mathbf{bb}(\|y\|) \geq BB(x) \geq m$ , which means  $\mathbf{bb}^{-1}(m) \leq \|y\| < n$ , causing a contradiction.  $\square$

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**Lemma 2**  $\mathbf{I}(f(a); \mathcal{H}) <^+ \mathbf{I}(a; \mathcal{H}) + \mathbf{K}(f)$ .

**Proof.**

$$\mathbf{I}(a; \mathcal{H}) = \mathbf{K}(a) - \mathbf{K}(a|\mathcal{H}) >^+ \mathbf{K}(a, f(a)) - \mathbf{K}(a, f(a)|\mathcal{H}) - \mathbf{K}(f).$$

The chain rule applied twice results in

$$\begin{aligned} \mathbf{I}(a; \mathcal{H}) + \mathbf{K}(f) &>^+ \mathbf{K}(f(a)) + \mathbf{K}(a|f(a), \mathbf{K}(f(a))) - (\mathbf{K}(f(a)|\mathcal{H}) + \mathbf{K}(a|f(a), \mathbf{K}(f(a)|\mathcal{H}), \mathcal{H})) \\ &=^+ \mathbf{I}(f(a); \mathcal{H}) + \mathbf{K}(a|f(a), \mathbf{K}(f(a))) - \mathbf{K}(a|f(a), \mathbf{K}(f(a)|\mathcal{H}), \mathcal{H}) \\ &=^+ \mathbf{I}(f(a); \mathcal{H}) + \mathbf{K}(a|f(a), \mathbf{K}(f(a))) - \mathbf{K}(a|f(a), \mathbf{K}(f(a)), \mathbf{K}(f(a)|\mathcal{H}), \mathcal{H}) \\ &>^+ \mathbf{I}(f(a); \mathcal{H}). \end{aligned}$$

□

**Lemma 3** A relation  $X = \{(x_i, c_i)\}_{i=1}^{2^n} \subset \{0, 1\}^* \times \mathbb{N}$ ,  $|\mathbf{K}(x_i) - c_i| \leq s$ , has  $n <^{\log} 2s + 2\mathbf{I}(X; \mathcal{H})$ .

**Proof.** We relativize the universal Turing machine to  $(n, s)$ , which can be done due to the precision of the theorem. Let  $T = \min\{t : \lceil -\log \mathbf{m}_t(x_i) \rceil - c_i < s + 1\}$ . Let  $N = \mathbf{bb}^{-1}(T)$  and  $M = \mathbf{bb}(N)$ . So for all  $x_i$ ,  $-\log \mathbf{m}_M(x_i) - \mathbf{K}(x_i) <^+ 2s$ . Let  $Q$  be an elementary probability measure that realizes  $\mathbf{Ks}(X)$  and  $d = \max\{\mathbf{d}(X|Q), 1\}$ . Without loss of generality, the support of  $Q$  is restricted to binary relations  $B \subset \{0, 1\}^* \times \mathbb{N}$  of size  $2^n$ . Let  $B_1 = \bigcup\{y : (y, c) \in B\}$ . Let  $S = \bigcup\{B_1 : B \in \text{Support}(Q)\}$ . We randomly select each string in  $S$  to be in a set  $R$  independently with probability  $d2^{-n}$ . Thus  $\mathbf{E}[\mathbf{m}_M(R)] \leq d2^{-n}$ . For  $B \in \text{Support}(Q)$ ,

$$\mathbf{E}_R \mathbf{E}_{B \sim Q}[[R \cap B_1 = \emptyset]] = \mathbf{E}_{B \sim Q} \Pr(R \cap B_1 = \emptyset) = (1 - d2^{-n})^{2^n} < e^{-d}.$$

Thus there exists a set  $R \subseteq S$  such that  $\mathbf{m}_M(R) \leq 2 \cdot 2^{-n}$  and  $\mathbf{E}_{B \sim Q}[[R \cap B_1 = \emptyset]] < 2e^{-d}$ . Let  $t(B) = .5[R \cap B_1 = \emptyset]2^d$ .  $t$  is a  $Q$ -test, with  $\mathbf{E}_{B \sim Q}[t(B)] \leq 1$ . It must be that  $t(X) \neq 0$ , otherwise,

$$1.44d - 1 < \log t(X) <^+ \mathbf{d}(X|Q) + \mathbf{K}(t|Q) <^+ d + \mathbf{K}(d),$$

which is a contradiction for large enough  $d$ , which one can assume without loss of generality. Thus  $t(X) \neq 0$  and  $R \cap X_1 \neq \emptyset$ . Furthermore, if  $y \in R$ ,  $\mathbf{K}(y) <^+ -\log \mathbf{m}_M(x) - n + \log d + \mathbf{K}(d, M, R)$ . So for  $x \in R \cap X_1$ ,

$$\begin{aligned} \mathbf{K}(x) &<^+ -\log \mathbf{m}_M(x) - n + \log d + \mathbf{K}(d, M, R) \\ \mathbf{K}(x) &<^+ \mathbf{K}(x) + 2s - n + \log d + \mathbf{K}(M) + \mathbf{K}(R, d) \\ n &<^+ 2s + \mathbf{K}(M) + \log d + \mathbf{K}(Q, d) \\ n &<^+ 2s + \mathbf{K}(\Omega[N]) + \mathbf{Ks}(X) \\ n &<^+ 2s + \mathbf{K}(\Omega[N]) + \mathbf{I}(X; \mathcal{H}) \end{aligned} \tag{1}$$

From Lemma 1,  $\mathbf{K}(\Omega[N]|T, N) =^+ \mathbf{K}(\Omega[N]|X, N) = O(1)$ . Furthermore it is well known for the bits of Chaitin's Omega,  $N <^+ \mathbf{K}(\Omega[N])$  and  $\mathbf{K}(\Omega[N]|\mathcal{H}) <^+ \mathbf{K}(N)$ . So, using Lemma 2,

$$N <^+ \mathbf{K}(\Omega[N]) <^{\log} \mathbf{I}(\Omega[N]; \mathcal{H}) <^{\log} \mathbf{I}(X; \mathcal{H}) + \mathbf{K}(N) <^{\log} \mathbf{K}(X; \mathcal{H}). \tag{2}$$

So combining Equations 1 and 2, one gets

$$n <^{\log} 2s + 2\mathbf{I}(X; \mathcal{H}).$$

□

### 3 Results

**Theorem 1** *If  $\mathbf{w}$  is a semimeasure on  $\{0, 1\}^*$  and  $\mathbf{m}^* < \mathbf{w}$  then  $\mathbf{I}(\mathbf{w} : \mathcal{H}) = \infty$ .*

**Proof.** Note that  $\mathbf{w}$  has full support since  $\mathbf{m}$  does. One can also assume that for each  $x \in \{0, 1\}^*$ ,  $-\log \mathbf{w}(x) \in \mathbb{N}$ . Let  $N \subseteq \mathbb{N}$  be a set of numbers  $n$  such that  $\mathbf{w}(\{0, 1\}^n) < 1/n$ . Obviously  $|N| = \infty$ . Fix  $n \in N$ . We have  $X_n = \{x : \mathbf{w}(x) < 2^{-n-\log n+O(1)}\}$ . Some simple math shows that  $|X_n| > 2^n$ . So for each  $x \in X_n$ ,  $\mathbf{K}(x) >^+ -\log \mathbf{w}(x) >^+ n + \log n$ . We also have that for each  $x \in \{0, 1\}^n$ ,  $\mathbf{K}(x) <^+ n + \mathbf{K}(n)$ . Let  $Y_n = \{(x, n + \log n) : x \in X_n\}$ . So for each  $(x, c) \in Y_n$ ,  $|\mathbf{K}(x) - c| <^+ \log n$ . So applying Lemma 3 to  $Y_n$ , we get  $n <^{\log} \mathbf{I}(Y_n; \mathcal{H}) <^{\log} \mathbf{I}(\mathbf{w} : \mathcal{H}) + \mathbf{K}(n) <^{\log} \mathbf{I}(\mathbf{w} : \mathcal{H})$ . Since  $|N| = \infty$ ,  $\mathbf{I}(\mathbf{w} : \mathcal{H}) = \infty$ .  $\square$

### References

- [Lev74] L. A. Levin. Laws of Information Conservation (Non-growth) and Aspects of the Foundations of Probability Theory. *Problemy Peredachi Informatsii*, 10(3):206–210, 1974.