

# Information Theory and Statistics

## Lecture 8: Complexity and entropy

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# Kolmogorov complexity and entropy

- Prefix-free complexity is the length of a prefix-free code.
- Hence we may expect that it can be related to entropy.

# Distribution of random variables

- Let  $(X_i)_{i \in \mathbb{N}}$  be a sequence of random variables,  $X_i : \Omega \rightarrow \Gamma$ .
- We denote its a probability distribution

$$P(x_1^m) = P(X_1^m = x_1^m).$$

- We will consider Kolmogorov complexity  $K(x_1^m | P)$ , which is the prefix-free Kolmogorov complexity of  $x_1^m$  given the definition of distribution of  $P$  on the infinite tape.
- If  $P$  is computable then

$$K(x_1^m | P) \stackrel{+}{<} K(x_1^m) \stackrel{+}{<} K(x_1^m | P) + K(P).$$

# Shannon-Fano coding

## Theorem

For any distribution  $\mathbf{P}$ ,

$$K(x_1^m | \mathbf{P}) \stackrel{+}{<} -\log \mathbf{P}(x_1^m) + 2 \log m.$$

## Proof

The inequality follows from the fact that a certain program that computes  $x_1^m$  has form “having the definition of  $\mathbf{P}$  and the length of string  $x_1^m$ , take the Shannon-Fano code word for  $x_1^m$  with respect to  $\mathbf{P}$  and compute  $x_1^m$  from it.”

# Source coding inequality

## Theorem (source coding inequality)

Let  $\mathbf{B} : \Gamma^m \rightarrow \Gamma^*$  be a prefix-free code. For any distribution  $\mathbf{P}$ ,

$$\sum_{\mathbf{x}_1^m} \mathbf{P}(\mathbf{x}_1^m) [|\mathbf{B}(\mathbf{x}_1^m)| + \log \mathbf{P}(\mathbf{x}_1^m)] \geq 0.$$

Since prefix-free Kolmogorov complexity is the length of a prefix-free code, we obtain the following result:

## Theorem

$$0 \leq \sum_{\mathbf{x}_1^m} \mathbf{P}(\mathbf{x}_1^m) [K(\mathbf{x}_1^m | \mathbf{P}) + \log \mathbf{P}(\mathbf{x}_1^m)] \stackrel{+}{<} 2 \log m.$$

# Barron theorem

## Theorem (Barron theorem)

Let  $\mathbf{B} : \Gamma^* \rightarrow \Gamma^*$  be a prefix-free code. For any distribution  $\mathbf{P}$ ,

$$\lim_{m \rightarrow \infty} [|\mathbf{B}(\mathbf{X}_1^m)| + \log \mathbf{P}(\mathbf{X}_1^m)] = \infty$$

holds with  $\mathbf{P}$ -probability 1.

Since prefix-free Kolmogorov complexity is the length of a prefix-free code, we obtain the following result:

## Theorem

$$0 \leq [K(\mathbf{X}_1^m | \mathbf{P}) + \log \mathbf{P}(\mathbf{X}_1^m)] \stackrel{+}{<} 2 \log m$$

holds for sufficiently large  $m$  with  $\mathbf{P}$ -probability 1.

# Markov inequality

## Theorem (Markov inequality)

Let  $\epsilon > 0$  be a fixed constant and let  $\mathbf{Y}$  be a random variable such that  $\mathbf{Y} \geq 0$ . We have

$$P(\mathbf{Y} \geq \epsilon) \leq \frac{E\mathbf{Y}}{\epsilon}.$$

## Proof

Consider random variable  $\mathbf{Z} = \mathbf{Y}/\epsilon$ . We have

$$P(\mathbf{Y} \geq \epsilon) = \int_{\mathbf{Z} \geq 1} dP \leq \int_{\mathbf{Z} \geq 1} \mathbf{Z} dP \leq \int \mathbf{Z} dP = \frac{E\mathbf{Y}}{\epsilon}.$$

# Borel-Cantelli lemma

Denote

$$\limsup_{n \rightarrow \infty} \mathbf{A}_n = \{\omega : \omega \in \mathbf{A}_m \text{ for infinitely many } \mathbf{m}\}.$$

We have

$$\left( \limsup_{n \rightarrow \infty} \mathbf{A}_n \right)^c = \{\omega : \omega \notin \mathbf{A}_m \text{ for sufficiently large } \mathbf{m}\}.$$

For proving that some events hold with probability **1**, the following proposition is particularly useful.

## Theorem (Borel-Cantelli lemma)

If  $\sum_{m=1}^{\infty} \mathbf{P}(\mathbf{A}_m) < \infty$  for a family of events  $\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3, \dots$  then

$$\mathbf{P} \left( \limsup_{n \rightarrow \infty} \mathbf{A}_n \right) = 0.$$



# Proof of the Borel-Cantelli lemma

Notice that  $\sum_{m=1}^{\infty} P(\mathbf{A}_m) < \infty$  implies

$$\lim_{m \rightarrow \infty} \sum_{k=m}^{\infty} P(\mathbf{A}_k) = 0.$$

Hence we obtain

$$\begin{aligned} & P(\{\omega : \omega \in \mathbf{A}_m \text{ for infinitely many } m\}) \\ &= P(\{\omega : \forall m \geq 1 \exists k \geq m \omega \in \mathbf{A}_k\}) \\ &= P\left(\bigcap_{m=1}^{\infty} \bigcup_{k=m}^{\infty} \mathbf{A}_k\right) \\ &\leq \inf_{m \geq 1} P\left(\bigcup_{k=m}^{\infty} \mathbf{A}_k\right) \leq \inf_{m \geq 1} \sum_{k=m}^{\infty} P(\mathbf{A}_k) = 0. \end{aligned}$$

# Proof of Barron theorem

Let us write

$$W(x_1^m) = \frac{2^{-|B(x_1^m)|}}{P(x_1^m)2^{-n}}.$$

By the Markov inequality we obtain

$$\begin{aligned} & \sum_{m=1}^{\infty} P(|B(X_1^m)| + \log P(X_1^m) \leq n) \\ &= \sum_{m=1}^{\infty} P(W(X_1^m) \geq 1) \\ &\leq \sum_{m=1}^{\infty} \sum_{x_1^m} P(x_1^m)W(x_1^m) = \sum_{m=1}^{\infty} \sum_{x_1^m} 2^{-|B(x_1^m)|+n} \end{aligned}$$

# Proof (continued)

Continuing, by the Kraft inequality we obtain,

$$\begin{aligned} \sum_{m=1}^{\infty} \mathbf{P} (|\mathbf{B}(\mathbf{X}_1^m)| + \log \mathbf{P}(\mathbf{X}_1^m) \leq n) \\ \leq \sum_{m=1}^{\infty} \sum_{x_1^m} 2^{-|\mathbf{B}(x_1^m)|+n} \leq 2^n < \infty. \end{aligned}$$

Hence from the Borel-Cantelli lemma we obtain that

$$|\mathbf{B}(\mathbf{X}_1^m)| + \log \mathbf{P}(\mathbf{X}_1^m) > n \text{ for sufficiently large } m$$

holds with  $\mathbf{P}$ -probability 1.

The  $n$  in this statement is arbitrary so the claim follows.

# An analogue of the chain rule

The parallels between prefix-free complexity and entropy can be drawn further. The following theorem is an analogue of the chain rule

$$H(X, Y) = H(X) + H(Y|X).$$

## Theorem

$$K(\langle u, w \rangle) \stackrel{\pm}{=} K(u) + K(w | \langle u, K(u) \rangle).$$

In the proposition above, it is easy to show that the left hand side is smaller than the right hand side. The proof of the converse inequality is harder.

# Partial proof of the chain rule

We will demonstrate that

$$K(\langle u, w \rangle) \stackrel{+}{\leq} K(u) + K(w | \langle u, K(u) \rangle).$$

Let  $\mathbf{p}$  be the shortest program that satisfies  $\mathbf{V}(\mathbf{p}) = \mathbf{u}$  and let  $\mathbf{p}'$  be the shortest program that satisfies  $\mathbf{V}(\mathbf{p}' | \langle \mathbf{u}, K(\mathbf{u}) \rangle) = \mathbf{w}$ . Then there exists a prefix-free machine  $\mathbf{S}$  that satisfies  $\mathbf{S}(\mathbf{pp}') = \langle \mathbf{u}, \mathbf{w} \rangle$ . Hence we obtain the claim.

# Incomplete analogy

In the algorithmic chain rule there appears term  $K(\mathbf{w} | \langle \mathbf{u}, K(\mathbf{u}) \rangle)$  rather than  $K(\mathbf{w} | \mathbf{u})$ . Although  $K(\mathbf{w} | \langle \mathbf{u}, K(\mathbf{u}) \rangle)$  differs from  $K(\mathbf{w} | \mathbf{u})$ , we can see that  $K(\langle \mathbf{u}, K(\mathbf{u}) \rangle)$  and  $K(\mathbf{u})$  are approximately equal.

## Theorem

$$K(\langle \mathbf{w}, K(\mathbf{w}) \rangle) \stackrel{\pm}{=} K(\mathbf{w}).$$

## Proof

From the shortest program that computes  $\mathbf{w}$ , we may reconstruct both  $\mathbf{w}$  and  $K(\mathbf{w})$ . Hence  $K(\langle \mathbf{w}, K(\mathbf{w}) \rangle) \stackrel{+}{<} K(\mathbf{w})$ . On the hand, we have  $K(\langle \mathbf{w}, K(\mathbf{w}) \rangle) \stackrel{+}{>} K(\mathbf{w})$  from a previous theorem.

# Algorithmic information

## Definition

We define *algorithmic information* between strings  $\mathbf{u}$  and  $\mathbf{w}$  as

$$I(\mathbf{u}; \mathbf{w}) = K(\mathbf{w}) - K(\mathbf{w} | \langle \mathbf{u}, K(\mathbf{u}) \rangle).$$

# Symmetry of algorithmic information

## Theorem

$$I(u; w) \stackrel{\pm}{=} I(w; u).$$

## Proof

Observe that

$$\begin{aligned} I(u; w) &= K(w) - K(w | \langle u, K(u) \rangle) \\ &\stackrel{\pm}{=} K(w) + K(u) - K(\langle u, w \rangle) \\ &\stackrel{\pm}{=} K(u) - K(u | \langle w, K(w) \rangle) = I(w; u). \end{aligned}$$