Chapter 2 General Data Compression Theorems

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Motivations

• We already know that the entropy rate

$$\lim_{n \to \infty} \frac{1}{n} H(X^n)$$

is the minimum data compression rate for arbitrarily small data compression error for block coding of the stationary ergodic source.

- We also mentioned that for a more complicated situation where the source becomes non-stationary, the quantity $\lim_{n\to\infty}(1/n)H(X^n)$ may not exist, and can no longer be used to characterize the source compression.
- This results in the need to establish a new entropy measure which appropriately characterizes the operational limits of arbitrary stochastic systems, which was done in the previous chapter.

• Here, we have made an implicit assumption in the following derivation, which is the source alphabet \mathcal{X} is *finite*.

Definition 2.1 (cf. Definition 3.2 and its associated footnote in [2]) An (n, M) block code for data compression is a set

$$\mathcal{C}_n := \{ \boldsymbol{c}_1, \boldsymbol{c}_2, \dots, \boldsymbol{c}_M \}$$

consisting of M sourcewords of block length n (and a binary-indexing codeword for each sourceword c_i).

Definition 2.2 Fix $\varepsilon \in [0, 1]$. *R* is an ε -achievable data compression rate for a source X if there exists a sequence of block data compression codes $\{\mathscr{C}_n = (n, M_n)\}_{n=1}^{\infty}$ with

$$\limsup_{n \to \infty} \frac{1}{n} \log M_n \le R,$$

and

$$\limsup_{n \to \infty} P_e(\mathcal{C}_n) \le \varepsilon,$$

where $P_e(\mathcal{C}_n) := \Pr(X^n \notin \mathcal{C}_n)$ is the probability of decoding error.

The infimum of all ε -achievable data compression rate for X is denoted by $T_{\varepsilon}(X)$.

- Note that in conventional source coding theorem, one wants to find the minimum rate with arbitrary small error. This rate is exactly $\lim_{\varepsilon \downarrow 0} T_{\varepsilon}(\mathbf{X})$.
- As expected, for DMS, $\lim_{\varepsilon \downarrow 0} T_{\varepsilon}(\mathbf{X}) = H(X)$. Actually, for DMS, $T_{\varepsilon}(\mathbf{X}) = H(X)$ for any $\varepsilon \in [0, 1)$.

Lemma 2.3 Fix a positive integer n. There exists an (n, M_n) source block code \mathcal{C}_n for P_{X^n} such that its error probability satisfies

$$P_e(\mathcal{C}_n) \leq \Pr\left[\frac{1}{n}h_{X^n}(X^n) > \frac{1}{n}\log M_n\right].$$

Proof: Observe that

$$1 \geq \sum_{\{x^{n} \in \mathcal{X}^{n} : (1/n)h_{X^{n}}(x^{n}) \leq (1/n)\log M_{n}\}} P_{X^{n}}(x^{n})$$

$$\geq \sum_{\{x^{n} \in \mathcal{X}^{n} : (1/n)h_{X^{n}}(x^{n}) \leq (1/n)\log M_{n}\}} \frac{1}{M_{n}}$$

$$\geq \left| \left\{ x^{n} \in \mathcal{X}^{n} : \frac{1}{n}h_{X^{n}}(x^{n}) \leq \frac{1}{n}\log M_{n} \right\} \right| \frac{1}{M_{n}}.$$

Therefore, $|\{x^n \in \mathcal{X}^n : (1/n)h_{X^n}(x^n) \le (1/n)\log M_n\}| \le M_n$. We can then choose a code

$$\mathscr{C}_n \supset \left\{ x^n \in \mathcal{X}^n : \frac{1}{n} h_{X^n}(x^n) \le \frac{1}{n} \log M_n \right\}$$

with $|\mathcal{L}_n| = M_n$ and

$$P_e(\mathscr{C}_n) = 1 - P_{X^n}\{\mathscr{C}_n\} \le \Pr\left[\frac{1}{n}h_{X^n}(X^n) > \frac{1}{n}\log M_n\right].$$

Lemma 2.4 Every (n, M_n) source block code \mathcal{C}_n for P_{X^n} satisfies

$$P_e(\mathscr{C}_n) \ge \Pr\left[\frac{1}{n}h_{X^n}(X^n) > \frac{1}{n}\log M_n + \gamma\right] - \exp\{-n\gamma\},$$

for every $\gamma > 0$.

Proof: It suffices to prove that

$$1 - P_e(\mathcal{C}_n) = \Pr\left\{X^n \in \mathcal{C}_n\right\} \le \Pr\left[\frac{1}{n}h_{X^n}(X^n) \le \frac{1}{n}\log M_n + \gamma\right] + \exp\{-n\gamma\}.$$

Clearly,

$$\Pr\{X^{n} \in \mathcal{C}_{n}\} = \Pr\left\{X^{n} \in \mathcal{C}_{n} \text{ and } \frac{1}{n}h_{X^{n}}(X^{n}) \leq \frac{1}{n}\log M_{n} + \gamma\right\}$$
$$+\Pr\left\{X^{n} \in \mathcal{C}_{n} \text{ and } \frac{1}{n}h_{X^{n}}(X^{n}) > \frac{1}{n}\log M_{n} + \gamma\right\}$$

$$\leq \Pr\left\{\frac{1}{n}h_{X^{n}}(X^{n}) \leq \frac{1}{n}\log M_{n} + \gamma\right\}$$
$$+ \Pr\left\{X^{n} \in \mathcal{C}_{n} \text{ and } \frac{1}{n}h_{X^{n}}(X^{n}) > \frac{1}{n}\log M_{n} + \gamma\right\}$$
$$= \Pr\left\{\frac{1}{n}h_{X^{n}}(X^{n}) \leq \frac{1}{n}\log M_{n} + \gamma\right\}$$
$$+ \sum_{x^{n} \in \mathcal{C}_{n}} P_{X^{n}}(x^{n}) \cdot \mathbf{1}\left\{\frac{1}{n}h_{X^{n}}(x^{n}) > \frac{1}{n}\log M_{n} + \gamma\right\}$$
$$= \Pr\left\{\frac{1}{n}h_{X^{n}}(X^{n}) \leq \frac{1}{n}\log M_{n} + \gamma\right\}$$
$$+ \sum_{x^{n} \in \mathcal{C}_{n}} P_{X^{n}}(x^{n}) \cdot \mathbf{1}\left\{P_{X^{n}}(x^{n}) < \frac{1}{M_{n}}\exp\{-n\gamma\}\right\}$$
$$< \Pr\left\{\frac{1}{n}h_{X^{n}}(X^{n}) \leq \frac{1}{n}\log M_{n} + \gamma\right\} + |\mathcal{C}_{n}|\frac{1}{M_{n}}\exp\{-n\gamma\}$$
$$= \Pr\left\{\frac{1}{n}h_{X^{n}}(X^{n}) \leq \frac{1}{n}\log M_{n} + \gamma\right\} + \exp\{-n\gamma\}.$$

We now apply Lemmas 2.3 and 2.4 to prove a *general* source coding theorems for block codes.

Theorem 2.5 (general source coding theorem) For any source X,

$$T_{\varepsilon}(\boldsymbol{X}) = \begin{cases} \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}), & \text{for } \varepsilon \in [0,1); \\ 0, & \text{for } \varepsilon = 1. \end{cases}$$

Proof: The case of $\varepsilon = 1$ follows directly from its definition; hence, the proof only focus on the case of $\varepsilon \in [0, 1)$.

1. Forward part (achievability): $T_{\varepsilon}(\mathbf{X}) \leq \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\mathbf{X})$

We need to prove the existence of a sequence of block codes $\{\mathscr{C}_n = (n, M_n)\}_{n \ge 1}$ such that for every $\gamma > 0$,

$$\limsup_{n \to \infty} \frac{1}{n} \log M_n \le \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}) + \gamma \quad \text{and} \quad \limsup_{n \to \infty} P_e(\mathcal{C}_n) \le \varepsilon.$$

Lemma 2.3 ensures the existence (for any $\gamma > 0$) of a source block code $\mathcal{C}_n = (n, M_n = \lceil \exp\{n(\lim_{\delta \uparrow (1-\varepsilon)} \overline{H}_{\delta}(\mathbf{X}) + \gamma)\} \rceil)$ with error probability

$$P_{e}(\mathscr{C}_{n}) \leq \Pr\left\{\frac{1}{n}h_{X^{n}}(X^{n}) > \frac{1}{n}\log M_{n}\right\}$$
$$\leq \Pr\left\{\frac{1}{n}h_{X^{n}}(X^{n}) > \lim_{\delta\uparrow(1-\varepsilon)}\bar{H}_{\delta}(\boldsymbol{X}) + \gamma\right\}$$

Therefore,

$$\limsup_{n \to \infty} P_e(\mathscr{C}_n) \leq \limsup_{n \to \infty} \Pr\left\{\frac{1}{n} h_{X^n}(X^n) > \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(X) + \gamma\right\}$$
$$= 1 - \liminf_{n \to \infty} \Pr\left\{\frac{1}{n} h_{X^n}(X^n) \leq \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(X) + \gamma\right\}$$
$$\leq 1 - (1 - \varepsilon) = \varepsilon,$$

where the last inequality follows from

$$\lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}) = \sup \left\{ \theta : \liminf_{n \to \infty} \Pr\left[\frac{1}{n} h_{X^n}(X^n) \le \theta\right] < 1-\varepsilon \right\}. \quad (2.1.1)$$

2. Converse part: $T_{\varepsilon}(\mathbf{X}) \geq \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\mathbf{X})$

Assume without loss of generality that $\lim_{\delta\uparrow(1-\varepsilon)} \bar{H}_{\delta}(\mathbf{X}) > 0$. We will prove the converse by contradiction. Suppose that $T_{\varepsilon}(\mathbf{X}) < \lim_{\delta\uparrow(1-\varepsilon)} \bar{H}_{\delta}(\mathbf{X})$. Then $(\exists \gamma > 0) T_{\varepsilon}(\mathbf{X}) < \lim_{\delta\uparrow(1-\varepsilon)} \bar{H}_{\delta}(\mathbf{X}) - 4\gamma$. By definition of $T_{\varepsilon}(\mathbf{X})$, there exists a sequence of codes $\mathscr{C}_n = (n, M_n)$ such that

$$\limsup_{n \to \infty} \frac{1}{n} \log M_n \le \left(\lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}) - 4\gamma \right) + \gamma < \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}) - 2\gamma \quad (2.1.2)$$

and

$$\limsup_{n \to \infty} P_e(\mathcal{C}_n) \le \varepsilon.$$
(2.1.3)

(2.1.2) implies that

$$\frac{1}{n}\log M_n \le \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}) - 2\gamma$$

for all sufficiently large n. Hence, for those n satisfying the above inequality and also by Lemma 2.4,

$$P_{e}(\mathscr{C}_{n}) \geq \Pr\left[\frac{1}{n}h_{X^{n}}(X^{n}) > \frac{1}{n}\log M_{n} + \gamma\right] - e^{-n\gamma}$$

$$\geq \Pr\left[\frac{1}{n}h_{X^{n}}(X^{n}) > \left(\lim_{\delta\uparrow(1-\varepsilon)}\bar{H}_{\delta}(\boldsymbol{X}) - 2\gamma\right) + \gamma\right] - e^{-n\gamma}.$$

Therefore,

$$\limsup_{n \to \infty} P_e(\mathscr{C}_n) \geq 1 - \liminf_{n \to \infty} \Pr\left[\frac{1}{n} h_{X^n}(X^n) \leq \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(X) - \gamma\right]$$

> $1 - (1 - \varepsilon) = \varepsilon,$

where the last inequality follows from (2.1.1). Thus, a contradiction to (2.1.3) is obtained. $\hfill \Box$

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A few remarks are made based on the previous theorem.

• Note that as $\varepsilon = 0$,

$$T_0(\boldsymbol{X}) = \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}) = \bar{H}(\boldsymbol{X}).$$

Hence, the minimum (asymptotic) lossless fixed-length source coding rate of any finite-alphabet source is $\bar{H}(\mathbf{X})$.

• Consider the special case where

$$-\frac{1}{n}\log P_{X^n}(X^n)$$
 converges in probability to a constant H (entropy rate),

which holds for all *information stable* sources. In this case, both the inf- and sup-spectrums of X degenerate to a unit step function:

$$u(\theta) = \begin{cases} 1, & \text{if } \theta > H; \\ 0, & \text{if } \theta < H. \end{cases}$$

Thus, $\bar{H}_{\varepsilon}(\mathbf{X}) = H$ for all $\varepsilon \in [0, 1)$. Hence, general source coding theorem reduces to the conventional source coding theorem.

– A source

$$\boldsymbol{X} = \left\{ X^n = \left(X_1^{(n)}, \dots, X_n^{(n)} \right) \right\}_{n=1}^{\infty}$$

is said to be *information stable* if

$$H(X^n) = E\left[-\log P_{X^n}(x^n)\right] > 0 \text{ for all } n,$$

and

$$\lim_{n \to \infty} \Pr\left(\left| \frac{-\log P_{X^n}(x^n)}{H(X^n)} - 1 \right| > \varepsilon \right) = 0,$$

for every $\varepsilon > 0$.

 By the definition, any stationary-ergodic source with finite n-fold entropy is information stable; hence, it can be viewed as a generalized source model for stationary-ergodic sources.

• If

 $-\frac{1}{n}\log P_{X^n}(X^n)$ converges in probability to a random variable Z whose cdf is $F_Z(\cdot)$, then the minimum achievable data compression rate subject to decoding error being no greater than ε is

$$T_{\varepsilon}(\boldsymbol{X}) = \lim_{\delta \uparrow (1-\varepsilon)} \bar{H}_{\delta}(\boldsymbol{X}) = \sup \{R : F_{Z}(R) < 1-\varepsilon\}$$

Example 2.6 Consider a binary source X with each X^n is Bernoulli(Θ) distributed, where Θ is a random variable defined over (0, 1). By ergodic decomposition theorem (which states that any stationary source can be viewed as a mixture of stationary-ergodic sources) that

$$-\frac{1}{n}\log P_{X^n}(X^n)$$
 converges in probability to $h_b(\Theta)$,

where $h_b(x) := -x \log_2(x) - (1-x) \log_2(1-x)$. Consequently,

$$T_{\varepsilon}(\boldsymbol{X}) = \sup\{R : \Pr\{h_b(\Theta) \le R\} < 1 - \varepsilon\}.$$

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- From the above example, or from Theorem 2.5, it shows that the *strong converse theorem* (which states that codes with rate below entropy rate will ultimately have decompression error approaching one) does not hold in general. However, one can always claim the *weak converse statement* for arbitrary sources.

Theorem 2.7 (weak converse theorem) For any block code sequence of ultimate rate $R < \overline{H}(X)$, the probability of block decoding failure P_e cannot be made arbitrarily small. In other words, there exists $\varepsilon > 0$ such that P_e is lower bounded by ε infinitely often in block length n.

Behavior of the probability of block decoding error as block length n goes to infinity for an *arbitrary* source X.

Generalized AEP theorem

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Theorem 2.8 (generalized asymptotic equipartition property for arbitrary sources) Fix $\varepsilon \in [0, 1)$. Given an arbitrary source X, define

$$\mathcal{T}_n[R] := \left\{ x^n \in \mathcal{X}^n : -\frac{1}{n} \log P_{X^n}(x^n) \le R \right\}.$$

Then for any $\delta > 0$, the following statements hold.

1.

$$\liminf_{n \to \infty} \Pr\left\{ \mathcal{T}_n[\bar{H}_{\varepsilon}(\boldsymbol{X}) - \delta] \right\} \le \varepsilon$$
(2.1.4)

2.

$$\liminf_{n \to \infty} \Pr\left\{ \mathcal{T}_n[\bar{H}_{\varepsilon}(\boldsymbol{X}) + \delta] \right\} > \varepsilon$$
(2.1.5)

3. The number of elements in

$$\mathcal{F}_n(\delta;\varepsilon) := \mathcal{T}_n[\bar{H}_{\varepsilon}(\boldsymbol{X}) + \delta] \setminus \mathcal{T}_n[\bar{H}_{\varepsilon}(\boldsymbol{X}) - \delta],$$

denoted by $|\mathcal{F}_n(\delta;\varepsilon)|$, satisfies

$$\left|\mathcal{F}_{n}(\delta;\varepsilon)\right| \leq \exp\left\{n(\bar{H}_{\varepsilon}(\boldsymbol{X})+\delta)\right\},\tag{2.1.6}$$

where the operation $\mathcal{A} \setminus \mathcal{B}$ between two sets \mathcal{A} and \mathcal{B} is defined by $\mathcal{A} \setminus \mathcal{B} := \mathcal{A} \cap \mathcal{B}^c$ with \mathcal{B}^c denoting the complement set of \mathcal{B} .

Generalized AEP theorem

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4. There exists $\rho = \rho(\delta) > 0$ and a subsequence $\{n_j\}_{j=1}^{\infty}$ such that

$$|\mathcal{F}_n(\delta;\varepsilon)| > \rho \cdot \exp\left\{n_j(\bar{H}_{\varepsilon}(\boldsymbol{X}) - \delta)\right\}.$$
(2.1.7)



Illustration of generalized AEP Theorem. $\mathcal{F}_n(\delta; \varepsilon) := \mathcal{T}_n[\bar{H}_{\varepsilon}(\mathbf{X}) + \delta] \setminus \mathcal{T}_n[\bar{H}_{\varepsilon}(\mathbf{X}) - \delta]$ is the dashed region.

<u>Generalized AEP theorem</u>

• The set

$$\mathcal{F}_{n}(\delta;\varepsilon) := \mathcal{T}_{n}[\bar{H}_{\varepsilon}(\boldsymbol{X}) + \delta] \setminus \mathcal{T}_{n}[\bar{H}_{\varepsilon}(\boldsymbol{X}) - \delta]$$

$$= \left\{ x^{n} \in \mathcal{X}^{n} : \left| -\frac{1}{n} \log P_{X^{n}}(x^{n}) - \bar{H}_{\varepsilon}(\boldsymbol{X}) \right| < \delta \right\}$$

$$\bigcup \left\{ x^{n} \in \mathcal{X}^{n} : -\frac{1}{n} \log P_{X^{n}}(x^{n}) = \bar{H}_{\varepsilon}(\boldsymbol{X}) + \delta \right\}$$

is nothing but the weakly δ -typical set.

- $q_n := \Pr{\{\mathcal{F}_n(\delta; \varepsilon)\}} > 0$ infinitely often in n.

$$|\mathcal{F}_n(\delta;\varepsilon)| \approx e^{n\bar{H}_{\varepsilon}(\boldsymbol{X})},$$

and the probability of each sequence in $\mathcal{F}_n(\delta;\varepsilon)$ can be estimated by $q_n \cdot \exp\{-n\bar{H}_{\varepsilon}(\boldsymbol{X})\}$.

• In particular, if \mathbf{X} is a stationary-ergodic source, then $\bar{H}_{\varepsilon}(\mathbf{X})$ is independent of $\varepsilon \in [0, 1)$ and, $\bar{H}_{\varepsilon}(\mathbf{X}) = \underline{H}_{\varepsilon}(\mathbf{X}) = H$ for all $\varepsilon \in [0, 1)$, where H is the source entropy rate

$$H = \lim_{n \to \infty} \frac{1}{n} E\left[-\log P_{X^n}(X^n)\right].$$

In this case, the generalized AEP reduces to the conventional AEP.