

# Universal Ensembles for Sample-Wise Lossy Compression

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# A Very Quick Overview

## *Universal lossless coding:*

- Davisson ('73): maximin+minimax universality; mixtures.
- Rissanen ('84): a converse for 'most' parameter values.
- Weinberger, Merhav & Feder ('94): 'semi-deterministic' analogue.
- Merhav & Feder ('95): parametric class  $\rightarrow$  general class.
- Many: extensions, improvements, relations to prediction, etc.

## A Very Quick Overview (Cont'd)

### *Universal lossy $d$ -semifaithful coding:*

- Zhang, Yang & Wei ('97): non-universal redundancy  $\geq \frac{\log n}{2n}$ ; achievable  $\leq \frac{\log n}{n}$ ; universality - larger constant.
- Yu & Speed ('93): weak universality.
- Ornstein & Shields ('90): stat. erg. sources, Hamming distortion.
- Kontoyiannis ('00): a.s. results – CLT, LIL, no-cost universality.
- Kontoyiannis & Zhang ('02):  $-\log \Pr\{D\text{-ball}\}$ .
- Mahmood & Wagner ('22): minimax distortion-universality.

# In This Work ...

We adopt the semi-deterministic paradigm of Weinberger, Merhav & Feder ('94) for lossy compression:

## Redundancy rates relative to the 'memoryless' empirical RDF

- Random coding using a mixture (Kontoyiannis & Zhang - '02).
- Asympt. accurate evaluation of  $\Pr\{D\text{-ball}\}$ .
- Universality w.r.t. the distortion measure.
- Converse.

## Sequences "with memory"

- Optimal length =  $-\log P_{LZ}\{D\text{-ball}\}$
- The main contribution is in the converse.
- Discussion

# Notation & Definitions

- Source sequence:  $\mathbf{x} = (x_1, \dots, x_n) \in \mathcal{X}^n$ ,  $|\mathcal{X}| = J$ .
- Reproduction sequence:  $\hat{\mathbf{x}} = (\hat{x}_1, \dots, \hat{x}_n) \in \hat{\mathcal{X}}^n$ ,  $|\hat{\mathcal{X}}| = K$ .
- Distortion measure:  $d : \mathcal{X} \times \hat{\mathcal{X}} \rightarrow \mathbb{R}^+$ ;  $d(\mathbf{x}, \hat{\mathbf{x}}) = \sum_i d(x_i, \hat{x}_i)$ .
- Encoder:  $\phi_n : \mathcal{X}^n \rightarrow \mathcal{G}_n \subset \{0, 1\}^*$ .
- Decoder:  $\psi_n : \mathcal{G}_n \rightarrow \mathcal{C}_n \subseteq \hat{\mathcal{X}}^n$ .
- $D$ -semifaithful code:  $\forall \mathbf{x} \in \mathcal{X}^n$ ,  $d(\mathbf{x}, \psi_n(\phi_n(\mathbf{x}))) \leq nD$ .
- Code ensemble: independent random selection under

$$W(\hat{\mathbf{x}}) = (K - 1)! \cdot \int_{\Omega} dQ \prod_{i=1}^n Q(\hat{x}_i).$$

- $D$ -sphere:  $\mathcal{S}(\mathbf{x}, D) = \{\hat{\mathbf{x}} : d(\mathbf{x}, \hat{\mathbf{x}}) \leq nD\}$ .
- $\mathcal{T}_n(P) = \{\text{all } \mathbf{x} \in \mathcal{X}^n \text{ with empirical distribution } P\}$ .

## A Key Lemma - Assessing $W[\mathcal{S}(\boldsymbol{x}, D)]$

Let  $\boldsymbol{x} \in \mathcal{T}_n(P)$  and define

$$F(s, Q) \triangleq - \sum_x P(x) \ln \left[ \sum_{\hat{x}} Q(\hat{x}) e^{-sd(x, \hat{x})} \right] - sD.$$

Then, it is well known that

$$R_d(D, P) = \sup_{s \geq 0} \min_Q F(s, Q) = \min_Q \sup_{s \geq 0} F(s, Q).$$

Let  $(s^*, Q^*)$  be the saddle-point that achieves  $R_d(D, P)$  and define

$$V(P, d) = \left| \det \left\{ \text{Hess} F(s^* + j\omega, Q) \Big|_{(0, Q^*)} \right\} \right|, \quad j = \sqrt{-1}.$$

## A Key Lemma - Assessing $W[\mathcal{S}(\mathbf{x}, D)]$ (Cont'd)

Suppose that  $\{d(j, k), 1 \leq j \leq J, 1 \leq k \leq K\}$  are **commensurable** and let  $\Delta$  be their largest common divisor, and define

$$T_n(P, d) = (K-1)! \cdot (2\pi)^{K/2-1} \cdot \frac{\Delta \exp\{-s^*[(nD) \bmod \Delta]\}}{(1 - e^{-s^* \Delta}) \sqrt{V(P, d)}},$$

If  $\{d(j, k), 1 \leq j \leq J, 1 \leq k \leq K\}$  are incommensurable, take  $\Delta \rightarrow 0$ :

$$T_n(P, d) = \frac{(K-1)! \cdot (2\pi)^{K/2-1}}{s^* \sqrt{V(P, d)}}.$$

**Lemma:**

$$W[\mathcal{S}(\mathbf{x}, D)] = \frac{T_n(P, d)}{n^{K/2}} \cdot \exp\{-nR_d(D, P)\} \cdot [1 - \epsilon_{P,d}(n)].$$

The exact pre-exponent is essential for an exact characterization of the code-length redundancy in the sequel.

# Main Analysis Tool - the Saddlepoint Method

Representing the unit step function  $U(t)$  as the inverse Laplace transform of  $1/z$ :

$$U(t) = \frac{1}{2\pi j} \int_{c-j\infty}^{c+j\infty} \frac{e^{zt}}{z} dz, \quad c > 0,$$

we have:

$$\begin{aligned} W[\mathcal{S}(\mathbf{x}, D)] &= (K-1)! \sum_{\{\hat{\mathbf{x}}: d(\mathbf{x}, \hat{\mathbf{x}}) \leq nD\}} \int_{\Omega} Q(\hat{\mathbf{x}}) dQ \\ &= (K-1)! \sum_{\hat{\mathbf{x}} \in \hat{\mathcal{X}}^n} U\left(nD - \sum_{i=1}^n d(x_i, \hat{x}_i)\right) \int_{\Omega} Q(\hat{\mathbf{x}}) dQ \\ &= \frac{(K-1)!}{2\pi j} \int_{c-j\infty}^{c+j\infty} \int_{\Omega} \frac{e^{-nF(z, Q)}}{z} \cdot dQ dz, \end{aligned}$$

and we select  $c = s^*$  to pass thru all saddle-points.



# A Universal Coding Scheme

- Generate  $\mathcal{C}_n$  with  $A^n$  independent random codewords ( $A > K$ ),  $\hat{\mathbf{X}}_i \sim W$ ,  $i = 1, 2, \dots, A^n$ .
- Reveal the codebook to both parties.
- Given  $\mathbf{x}$  and  $d$ , find  $I_d(\mathbf{x}) = \min\{i : \hat{\mathbf{X}}_i \in \mathcal{S}(\mathbf{x}, D)\}$ .
- Encode  $I_d(\mathbf{x})$  using a Shannon code w.r.t. the distribution  $u[i] \propto 1/i$ ,  $i = 1, 2, \dots, A^n$ .
- The decoder decodes  $I_d(\mathbf{x})$  and outputs the  $I_d(\mathbf{x})$ -th reproduction vector from  $\mathcal{C}_n$ .

Note that the codebook is the same for every (bounded)  $d$  – distortion-universality.

# Coding Theorem

$\forall \epsilon > 0$ ,  $\exists$  a sequence of codebooks,  $\{\mathcal{C}_n\}_{n \geq 1}$ , and  $\{\psi_n\}$ , such that  $\forall d \in \bigcup_{k \geq 1} \{0, d_{\max}/k, \dots, d_{\max}\}^{JK}$ ,  $\exists \{\phi_n\}$ , such that  $\forall P \in \bigcup_{k \geq 1} \mathcal{P}_k$ ,  $n \in \mathcal{N} \triangleq \{\hat{n} : d \in \mathcal{D}_{\hat{n}}, P \in \mathcal{P}_{\hat{n}}\}$  and  $\mathbf{x} \in \mathcal{T}_n(P)$ :

(a)

$$L_d(\mathbf{x}) \leq nR_d(D, P) + \left(\frac{K}{2} + 2 + \epsilon\right) \cdot \ln n + \beta_{P,d}(n) + \log(\log A + 1) + O(J^n e^{-n^{1+\epsilon}}).$$

(b) The code is  $d$ -semifaithful:  $d(\mathbf{x}, \psi_n(\phi_n(\mathbf{x}))) \leq nD$ .

$\mathcal{C}_n$  and  $\psi_n$  do not depend on  $P$  and  $d$ , but  $\phi_n$  does.

Mahmood & Wagner ('22): 3 schemes with  $\log n$ -coefficients:  $2JK + J + 3$ ,  $J(K + 1)$  and  $J^2K^2 + J - 2$ .

# Converse Theorem

Let  $P$  and  $d$  be given.  $\forall \epsilon > 0$  and sufficiently large  $n$ ,  $\forall$  codebook that covers  $\mathcal{T}_n(P)$  and every one-to-one variable-length code applied to that codebook, the following lower bound applies to a fraction of at least  $(1 - 2n^{-\epsilon})$  of the codewords that cover  $\mathcal{T}_n(P)$ :

$$L_d(\hat{\mathbf{x}}) \geq nR_d(D, P) + \left(\frac{1}{2} - \epsilon\right) \log n + c - c' \log(\log n),$$

where  $c$  and  $c'$  are constants that depend on  $P$ .

## Converse Theorem (Cont'd)

The proof is based on a sphere-covering argument:

$$\log |\mathcal{T}_n(P)| \geq nH(P) - \frac{J-1}{2} \log n + c(P)$$

and

$$\begin{aligned} & \ln \left| \mathcal{T}_n(P) \cap \{ \mathbf{x} : d(\mathbf{x}, \hat{\mathbf{x}}) \leq nD \} \right| \\ & \leq \max_{\{P_{\hat{X}|X} : \mathbf{E}\{d(X, \hat{X})\} \leq D\}} H(X|\hat{X}) - \frac{J}{2} \log n + c' \log(\log n), \quad P_X = P \end{aligned}$$

and so,

$$|\mathcal{C}_n| \geq \exp_2 \left\{ nR_d(D, P) + \frac{\log n}{2} + \dots \right\}.$$

Most codewords cannot have code-length much less than  $\log |\mathcal{C}_n|$ .

# Beyond the Memoryless Structure

Consider the universal distribution

$$U(\hat{\mathbf{x}}) = \frac{2^{-LZ(\hat{\mathbf{x}})}}{\sum_{\hat{\mathbf{x}}'} 2^{-LZ(\hat{\mathbf{x}}')}}$$

and let

$$U[\mathcal{S}(\mathbf{x}, D)] = \sum_{\hat{\mathbf{x}} \in \mathcal{S}(\mathbf{x}, D)} U(\hat{\mathbf{x}}).$$

**Converse theorem:** Let  $\ell$  divide  $n$  and let  $\mathcal{T}_n(\hat{P}^\ell)$  be any  $\ell$ -th order type of source sequences. Let  $d$  be a distortion function that depends on  $(\mathbf{x}, \hat{\mathbf{x}})$  only via  $\hat{P}_{\mathbf{x}\hat{\mathbf{x}}}^1$ . Then,  $\forall$   $d$ -semifaithful variable-length block code, and  $\forall \epsilon > 0$ , the following lower bound applies to a fraction of at least  $(1 - 2n^{-\epsilon})$  of the codewords,  $\{\phi_n(\mathbf{x}), \mathbf{x} \in \mathcal{T}_n(\hat{P}^\ell)\}$ :

$$L(\phi_n(\mathbf{x})) \geq -\log(U[\mathcal{S}(\mathbf{x}, D)]) - n\Delta_n(\ell) - \epsilon \log n,$$

where  $\lim_{n \rightarrow \infty} \Delta_n(\ell) = 1/\ell$ .

# Main Ideas of the Proof

Relating sphere-covering and  $U[\mathcal{S}(\mathbf{x}, D)]$  in a few steps.

First, observe that

$$\begin{aligned} N(D) &\triangleq \sum_{\mathbf{x}, \hat{\mathbf{x}}} \mathcal{I}\{\mathbf{x} \in \mathcal{T}_n(P^\ell), \hat{\mathbf{x}} \in \mathcal{T}_n(Q^\ell), d(\mathbf{x}, \hat{\mathbf{x}}) \leq nD\} \\ &= |\mathcal{T}_n(P^\ell)| \cdot \left| T_n(Q^\ell) \cap \mathcal{S}(\mathbf{x}, D) \right| \\ &= |\mathcal{T}_n(Q^\ell)| \cdot \left| T_n(P^\ell) \cap \hat{\mathcal{S}}(\hat{\mathbf{x}}, D) \right|, \quad \hat{\mathcal{S}}(\hat{\mathbf{x}}, D) \triangleq \{\mathbf{x} : d(\mathbf{x}, \hat{\mathbf{x}}) \leq nD\} \end{aligned}$$

and so,

$$\frac{|\mathcal{T}_n(P^\ell)|}{\left| T_n(P^\ell) \cap \hat{\mathcal{S}}(\hat{\mathbf{x}}, D) \right|} = \frac{|\mathcal{T}_n(Q^\ell)|}{\left| T_n(Q^\ell) \cap \mathcal{S}(\mathbf{x}, D) \right|}$$

LHS = sphere-covering ratio;

RHS =  $1/U_Q[\mathcal{S}(\mathbf{x}, D)] \geq 1/U[\mathcal{S}(\mathbf{x}, D)] \rightarrow$  use  $U$  for random coding!

# Direct Theorem

Let  $d : \mathcal{X}^n \times \hat{\mathcal{X}}^n \rightarrow \mathbb{R}^+$  be an arbitrary distortion function. Then,  $\forall \epsilon > 0$ ,  $\exists$  sequence of  $d$ -semifaithful, variable-length block codes of block length  $n$ , such that  $\forall \mathbf{x} \in \mathcal{X}^n$ , the code length for  $\mathbf{x}$  is upper bounded by

$$L(\mathbf{x}) \leq -\log(U[\mathcal{S}(\mathbf{x}, D)]) + (2 + \epsilon) \log n + c + \delta_n,$$

where  $c > 0$  is a constant and  $\delta_n = O(nJ^n e^{-n^{1+\epsilon}})$ .

The proof is very similar to that of the previous direct theorem.

# Discussion

♠ Related to the Kontoyiannis-Zhang converse:

$$\forall \mathbf{x}, \mathbb{C}_n \exists Q : L(\mathbf{x}) \geq -\log Q[\mathcal{S}(\mathbf{x}, D)].$$

♠  $-\log(U[\mathcal{S}(\mathbf{x}, D)]) \sim \min_L \{L - \log |\{\hat{\mathbf{x}} : LZ(\hat{\mathbf{x}}) = L\} \cap \mathcal{S}(\mathbf{x}, D)|\}$ , analogous to  $\min_{P_{\hat{X}}} [H(\hat{X}) - \max\{H(\hat{X}|X) : \mathbf{E}d(X, \hat{X}) \leq D\}]$ .

♠ Easy to see that the proposed scheme is better than  $\min_{\hat{\mathbf{x}} \in \mathcal{S}(\mathbf{x}, D)} LZ(\hat{\mathbf{x}})$ . Complexity of both schemes depend on  $D$ .

♠ Universality w.r.t. a wide (continuous, parametric) class of distortion measures can also be proved. Here, the class distortion measures is quite arbitrary.