

Lecture 13, Part 1: Channel Coding and Source/Channel Separation

Robert Bamler • Summer Term of 2023

These slides are part of the course "Data Compression With and Without Deep Probabilistic Models" taught at University of Tübingen. More course materials—including video recordings, lecture notes, and problem sets with solutions—are publicly available at https://robamler.github.io/teaching/compress23/.

Recall: Two Theorems That Are Awaiting Proofs

▶ Rate/Distortion Theorem: $X \longrightarrow S \in \{0, 1\}^n \longrightarrow X'$

all lossy compression codes that satisfy $\mathbb{E}_{P}[d(\mathbf{X}, \mathbf{X}')] \leq \mathcal{D}$ have $\mathbb{E}_{P}[bit rate] \geq \mathcal{R}(\mathcal{D})$ with the rate/distortion curve:

$$\mathcal{R}(\mathcal{D}) := \inf_{\substack{P(\mathbf{X}'|\mathbf{X}):\ \mathbb{E}_P[d(\mathbf{X},\mathbf{X}')] \leq \mathcal{D}}} I_P(\mathbf{X};\mathbf{X}')$$

► Channel Coding Theorem: S ∈ {0,1}ⁿ → X ∈ X^k → Y' ∈ Y^k → S' ∈ {0,1}ⁿ In the limit of long messages (n ≫ 1), there exists a channel coding scheme that satisfies both of the following:

- the ratio $\frac{n}{k}$ can be made arbitrarily close to the channel capacity $C := \sup I_P(X_i; Y_i)$; and
- ▶ the error probability $P(\mathbf{S}' \neq \mathbf{s} | \mathbf{S} = \mathbf{s})$ can be made arbitrarily small for all $\mathbf{s} \in \{0, 1\}^n$.

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Recall: Typicality and Joint Typicality

► Def. typical set: $T_{P(X_i),k,\beta} := \left\{ \mathbf{x} \in \mathcal{X}^k \text{ that satisfty: } \left| \frac{-\log_2 P(\mathbf{X}=\mathbf{x})}{k} - H_P(X_i) \right| < \beta \right\}$

- most (long) messages are *not* typical: $|T_{P(X_i),k,\beta}| < 2^{k(H_P(X_i)+\beta)} \implies \frac{|T_{P(X_i),k,\beta}|}{|\mathcal{X}^k|} < 2^{k(H_P(X_i)-|\mathcal{X}|+\beta)}$
- But: most (long) random messages are typical: $P(\mathbf{X} \in T_{P(X_i),k,\beta}) \ge 1 \frac{\sigma^2}{k\beta^2} \xrightarrow{k \to \infty} 1$
- Def. joint typicality:

 $(\mathbf{x}, \mathbf{y}) \in J_{P(X_i, Y_i), k, \beta}$ iff: $\mathbf{x} \in T_{P(X_i), k, \beta}$, $\mathbf{y} \in T_{P(Y_i), k, \beta}$, and $(\mathbf{x}, \mathbf{y}) \in T_{P(X_i, Y_i), k, \beta}$.

- Again, most random samples $(\mathbf{x}, \mathbf{y}) \sim P(\mathbf{X}, \mathbf{Y})$ are jointly typical.
- ► Thus, if we draw x ~ P(X) and then transmit it over the noisy channel to get y ~ P(Y | X = x), the resulting pair (x, y) is jointly typical with high probability.
- ► But: drawing x ~ P(X) and y ~ P(Y) independently from their marginal distributions usually does not lead to joint typicality:

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Random Channel Codes



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$$\mathbf{S} \in \{0,1\}^n \xrightarrow{\text{channel encoder}} \mathbf{X} \in \mathcal{X}^k \xrightarrow{\text{memoryless channel}}_{\prod_{i=1}^k P(Y_i|X_i)} \mathbf{Y}' \in \mathcal{Y}^k \xrightarrow{\text{channel decoder}} \mathbf{S}' \in \{0,1\}^n$$

(Crazy) idea: assign random code words to bit strings:

- ▶ For each $\mathbf{s} \in \{0,1\}^n$, draw a code word $\mathcal{C}(\mathbf{s}) \in \mathcal{X}^k$ from $P(\mathbf{X})$.
- Define a (deterministic) channel encoder: $P(\mathbf{X} = \mathbf{x} | \mathbf{S} = \mathbf{s}, C) = \delta_{\mathbf{x}, C(\mathbf{s})}$.
- Channel decoder: map **y** to **s**' if $(\mathcal{C}(\mathbf{s}'), \mathbf{y}) \in J_{P(X_i, Y_i), k, \beta}$ for exactly one **s**'. Otherwise fail.
- Claim (Problem Set): In expectation over all random codes C that are constructed in this way, and over all input strings s ~ P(S) := Uniform({0,1}^k), the error probability for long messages goes to zero as long as ⁿ/_k < I_P(X_i, Y_i) − 3β.

Proof of Expected Performance of Random Codes

Claim: $\mathbb{E}_{P(\mathcal{C})P(S)}[P(S' \neq S | S, \mathcal{C})] \xrightarrow{k \to \infty} 0 \text{ if } \frac{n}{k} < I_P(X_i, Y_i) - 3\beta \quad (P(S) = \text{Uniform}(\{0, 1\}^n))$

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- 2 possibilities for errors:
 - $\blacktriangleright (\mathcal{C}(\mathbf{s}), \mathbf{y}) \notin J_{P(X_i, Y_i), k, \beta}:$
 - $(\mathcal{C}(\mathbf{s}'), \mathbf{y}) \in J_{P(X_i, Y_i), k, \beta}$ for some $\mathbf{s}' \neq \mathbf{s}$:
- Total error probability:

Proof of the Noisy Channel Coding Theorem

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Theorem (reminder): for long messages $(n \gg 1)$, there exists a channel coding scheme such that $\frac{n}{k}$ can be made arbitrarily close to the channel capacity C and the error probability $P(\mathbf{S}' \neq \mathbf{s} | \mathbf{S} = \mathbf{s})$ can be made arbitrarily small for all $\mathbf{s} \in \{0, 1\}^n$.

- Set $P(X_i) := \operatorname{arg max}_{P(X_i)} I_P(X_i; Y_i)$. Thus, $I_P(X_i; Y_i) = C$
- ► Assume $\frac{n}{k} < C 3\beta$. Thus, $\mathbb{E}_{P(\mathcal{C})P(\mathbf{S})} [P(\mathbf{S}' \neq \mathbf{S} \mid \mathbf{S}, \mathcal{C})] \xrightarrow{n \to \infty} 0$.

• This means that $\forall \varepsilon > 0 : \exists n_0$ such that $\mathbb{E}_{P(\mathcal{C})P(\mathbf{S})} [P(\mathbf{S}' \neq \mathbf{S} \mid \mathbf{S}, \mathcal{C})] < \frac{\varepsilon}{2} \forall n > n_0.$

- ⇒ For all $n > n_0$, there exists at least one code C with $\mathbb{E}_{P(\mathbf{S})}[P(\mathbf{S}' \neq \mathbf{S} | \mathbf{S}, C)] < \frac{\varepsilon}{2}$. ⇒ Since $P(\mathbf{S})$ is a uniform distribution over 2^n bit strings, the $2^n/2 = 2^{n-1}$ bit strings **s**
 - with lowest $P(S' \neq s | S = s, C)$ must all satisfy $P(S' \neq s | S = s, C) < \varepsilon$.
- \implies Use their 2^{n-1} code words $\mathcal{C}(\mathbf{s})$ to define a code with ratio $\frac{n-1}{k}$ ($\approx \frac{n}{k}$ for $n \to \infty$)
- Thus, we can make $\frac{n}{k}$ arbitrarily close to the capacity C by letting $\beta \to 0$.

Recall: Agenda

• Rate/Distortion Theorem: $X \longrightarrow S \in \{0, 1\}^n \longrightarrow X'$

all lossy compression codes that satisfy $\mathbb{E}_{P}[d(\mathbf{X}, \mathbf{X}')] \leq \mathcal{D}$ have $\mathbb{E}_{P}[\text{bit rate}] \geq \mathcal{R}(\mathcal{D})$ with the rate/distortion curve:

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- Channel Coding Theorem: $\mathbf{S} \in \{0, 1\}^n \longrightarrow \mathbf{X} \in \mathcal{X}^k \longrightarrow \mathbf{Y}' \in \mathcal{Y}^k \longrightarrow \mathbf{S}' \in \{0, 1\}^n$ In the limit of long messages $(n \gg 1)$, there exists a channel coding scheme that satisfies both of the following:
 - ▶ the ratio $\frac{n}{k}$ can be made arbitrarily close to the channel capacity $C := \sup I_P(X_i; Y_i)$; and
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- Channel coding: $\mathbf{S} \in \{0,1\}^n \xrightarrow{\text{encoder}}_{P(\mathbf{Y}|\mathbf{X})} \mathbf{X} \in \mathcal{X}^k \xrightarrow{\text{channel}}_{\prod_{i=1}^k P(Y_i|X_i)} \mathbf{Y}' \in \mathcal{Y}^k \xrightarrow{\text{decoder}}_{P(\mathbf{X}'|\mathbf{Y})} \mathbf{S}' \in \{0,1\}^n$
- (Lossy) source coding: $\mathbf{X} \xrightarrow{\text{encoder}}_{P(\mathbf{S}|\mathbf{X})} \mathbf{S} \in \{0,1\}^n \xrightarrow{\text{decoder}}_{P(\mathbf{X}'|\mathbf{S})} \mathbf{X}'$
 - Assume data source $P(\mathbf{X})$ and mapping $P(\mathbf{X}'|\mathbf{X})$ are both given.

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source

coding

Idea: consider inference channel $P(\mathbf{X}|\mathbf{X}') = \frac{P(\mathbf{X})P(\mathbf{X}'|\mathbf{X})}{\sum_{\mathbf{X}}P(\mathbf{X})P(\mathbf{X}'|\mathbf{X})}$

Source/Channel Separation Theorem

▶ We'll prove in Lecture 10 that one can (in principle) always use a more modular setup.

Preview: Source-Channel Separation Theorem

Recall from very first lecture:

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coding

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