COMP2610 – Information Theory Lecture 12: The Source Coding Theorem

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A General Communication Game

Data compression is the process of replacing a message with a smaller message which can be reliably converted back to the original.

- Sender & Receiver agree on code for each outcome ahead of time (e.g., 0 for *Heads*; 1 for *Tails*)
- Sender observes outcomes then codes and sends message
- Receiver decodes message and recovers outcome sequence
- Want small messages on average when outcomes are from a fixed, known, but uncertain source (e.g., coin flips with known bias)



Source Code

Given an ensemble X, the function $c : A_X \to B$ is a **source code** for X. The number of symbols in c(x) is the **length** l(x) of the codeword for x. The **extension** of c is defined by $c(x_1 \dots x_n) = c(x_1) \dots c(x_n)$

Smallest δ -sufficient subset

Let X be an ensemble and for $\delta \geq 0$ define S_{δ} to be the smallest subset of \mathcal{A}_X such that

$$P(x \in S_{\delta}) \geq 1 - \delta$$

Essential Bit Content

Let X be an ensemble then for $\delta \ge 0$ the **essential bit content** of X is

$$H_{\delta}(X) \stackrel{\text{\tiny def}}{=} \log_2 |S_{\delta}|$$

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A Note on Lossy Codes & Missing Codewords

When talking about a uniform lossy code c for $\mathcal{A}_X = \{a, b, c\}$ we write

$$c(a) = 0$$
 $c(b) = 1$ $c(c) = -$

where the symbol – means "no codeword". This is shorthand for "the receiver will decode this codeword incorrectly".

For the purposes of these lectures, this is equivalent to the code

$$c(a) = 0$$
 $c(b) = 1$ $c(c) = 1$

and the sender and receiver agreeing that the codeword 1 should always be decoded as b.

Assigning the outcome a_i the missing codeword "-" just means "it is not possible to send a_i reliably".

Our aim this week is to understand this:

The Source Coding Theorem

Let X be an ensemble with entropy H = H(X) bits. Given $\epsilon > 0$ and $0 < \delta < 1$, there exists a positive integer N_0 such that for all $N > N_0$

$$\left|\frac{1}{N}H_{\delta}\left(X^{N}\right)-H\right|<\epsilon.$$

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In English:

• Given outcomes drawn from X ...

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• ... have an average essential bit content $\frac{1}{N}H_{\delta}(X^{N})$ within ϵ of H(X) $H_{\delta}(X^{N})$ measures the *fewest* number of bits needed to uniformly code *smallest* set of *N*-outcome sequence S_{δ} with $P(x \in S_{\delta}) \ge 1 - \delta$.



Quick Review

2 Extended Ensembles

- Defintion and Properties
- Essential Bit Content

3 The Source Coding Theorem

- Statement of the Theorem
- Typical Sets
- The Asymptotic Equipartition Property

Extended Ensembles (Review)

Instead of coding single outcomes, we now consider coding blocks and sequences of blocks

Example (Coin Flips):

$hhhhthhthh \rightarrow$	• hh	hh	th	ht	ht	hh
—	hh]	h ht	th 1	nth	thł	1
;	hh]	hh 1	thht	t ht	thh	

- $(6 \times 2 \text{ outcome blocks})$
- $(4 \times 3 \text{ outcome blocks})$
- $(3 \times 4 \text{ outcome blocks})$

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ightarrow hhh hth hth thh	(4 ×
ightarrow hhhh thht hthh	(3 ×

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Extended Ensemble

The **extended ensemble** of blocks of size *N* is denoted X^N . Outcomes from X^N are denoted $\mathbf{x} = (x_1, x_2, \dots, x_N)$. The **probability** of \mathbf{x} is defined to be $P(\mathbf{x}) = P(x_1)P(x_2) \dots P(x_N)$.

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$\tt hhhhthhthh \to hh hh th ht hh$	(6 $ imes$ 2 outcome blocks)
ightarrow hhh hth hth thh	(4 $ imes$ 3 outcome blocks)
ightarrow hhhh thht hthh	(3 imes 4 outcome blocks)

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What is the entropy of X^N ?

Extended Ensembles (Review) Example: Bent Coin



Let X be an ensemble with outcomes $\mathcal{A}_X = \{h, t\}$ with $p_h = 0.9$ and $p_t = 0.1$.

Consider X^4 – i.e., 4 flips of the coin.

 $\mathcal{A}_{X^4} = \{\texttt{hhhh}, \texttt{hhht}, \texttt{hhth}, \dots, \texttt{tttt}\}$

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What is the probability of

- Four heads? $P(\text{hhhh}) = (0.9)^4 \approx 0.656$
- Four tails? $P(tttt) = (0.1)^4 = 0.0001$

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What is the entropy and raw bit content of X^4 ?

- The outcome set size is $|\mathcal{A}_{X^4}| = |\{0000, 0001, 0010, \dots, 1111\}| = 16$
- Raw bit content: $H_0(X^4) = \log_2 |\mathcal{A}_{X^4}| = 4$
- Entropy: $H(X^4) = 4H(X) = 4. (-0.9 \log_2 0.9 0.1 \log_2 0.1) = 1.88$



$$\delta=0$$
 gives $\mathit{H}_{\delta}\left(X^{4}
ight)=\log_{2}16=4$

What if we use a lossy uniform code on the extended ensemble?



 $\delta=0.0001$ gives $H_{\delta}\left(X^{4}
ight)=\log_{2}15=3.91$



$$\delta = 0.005$$
 gives $H_{\delta}\left(X^{4}
ight) = \log_{2}11 = 3.46$



$$\delta = 0.05$$
 gives $H_{\delta}\left(X^{4}
ight) = \log_{2}5 = 2.32$



$$\delta=$$
 0.25 gives $H_{\delta}\left(X^{4}
ight)=\log_{2}3=$ 1.6



$$\delta = 0.25$$
 gives $H_{\delta} (X^4) = \log_2 3 = 1.6$
Unlike entropy, $H_{\delta}(X^4) \neq 4H_{\delta}(X) = 0$

What happens as N increases?



Recall that the entropy of a single coin flip with $p_{\rm h}=0.9$ is H(X)pprox 0.47

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- The Asymptotic Equipartition Property

The Source Coding Theorem

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$$\left|\frac{1}{N}H_{\delta}\left(X^{N}\right)-H\right|<\epsilon.$$



- Given a tiny probability of error δ, the average bits per outcome can be made as close to H as required.
- Even if we allow a large probability of error we cannot compress more than *H* bits per outcome for large sequences.

Typical Sets and the AEP (Review)

Typical Set

For "closeness" $\beta > 0$ the typical set $T_{N\beta}$ for X^N is

$$T_{N\beta} \stackrel{\text{\tiny def}}{=} \left\{ \mathbf{x} : \left| -\frac{1}{N} \log_2 P(\mathbf{x}) - H(X) \right| < \beta \right\}$$

The name "typical" is used since $\mathbf{x} \in T_{N\beta}$ will have roughly p_1N occurences of symbol a_1 , p_2N of a_2 , ..., p_KN of a_K .

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Asymptotic Equipartition Property (Informal)

As $N \to \infty$, $\log_2 P(x_1, \ldots, x_N)$ is close to -NH(X) with high probability.

For large block sizes "almost all sequences are typical" (i.e., in $T_{N\beta}$). This means $T_{N\beta}$ can be made to "look like" S_{δ} for any δ by choosing N large enough. This is useful since $T_{N\beta}$ is easy to count (size $\approx 2^{NH(X)}$) while S_{δ} is not (size varies with distribution)

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Proof Idea: As *N* increases

- $T_{N\beta}$ has $\sim 2^{NH(X)}$ elements
- almost all **x** are in $T_{N\beta}$
- S_{δ} and $T_{N\beta}$ increasingly overlap
- so $\log_2 |S_\delta| \sim NH$

Proof of the SCT

The absolute value of a difference being bounded (e.g., $|x - y| \le \epsilon$) says two things:

- **()** When x y is positive, it says $x y < \epsilon$ which means $x < y + \epsilon$
- **2** When x y is negative, it says $-(x y) < \epsilon$ which means $x < y \epsilon$

 $|x - y| < \epsilon$ is equivalent to $y - \epsilon < x < y + \epsilon$

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Using this, we break down the claim of the SCT into two parts: showing that for any ϵ and δ we can find N large enough so that:

Part 1:
$$\frac{1}{N}H_{\delta}(X^{N}) < H + \epsilon$$

Part 2: $\frac{1}{N}H_{\delta}(X^{N}) > H - \epsilon$

For $\epsilon > 0$ and $\delta > 0$, want N large enough so $\frac{1}{N}H_{\delta}(X^N) < H(X) + \epsilon$.

Recall (see Lecture 10) for the *typical set* $T_{N\beta}$ we have for any N, β that

$$|T_{N\beta}| \le 2^{N(H(X)+\beta)} \tag{1}$$

and, by the AEP, for any β as $N \to \infty$ we have $P(x \in T_{N\beta}) \to 1$. So for any $\delta > 0$ we can always find an N such that $P(x \in T_{N\beta}) \ge 1 - \delta$.

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Now recall the definition of the *smallest* δ -sufficient subset S_{δ} : it is the smallest subset of outcomes such that $P(x \in S_{\delta}) \ge 1 - \delta$ so $|S_{\delta}| \le |T_{N\beta}|$.

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$$\log_2 |S_{\delta}| \leq \log_2 |T_{N\beta}| \leq N(H(X) + \beta)$$

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$$H_{\delta}(X^{N}) = \log_{2}|S_{\delta}| \le \log_{2}|T_{N\beta}| \le N(H(X) + \beta)$$

Setting $\beta = \epsilon$ and dividing through by N gives result.

For $\epsilon > 0$ and $\delta > 0$, want *N* large enough so $\frac{1}{N}H_{\delta}(X^N) > H(X) - \epsilon$. Suppose this was not the case – that is, for every *N* we have

$$\frac{1}{N}H_{\delta}(X^{N}) \leq H(X) - \epsilon \iff |S_{\delta}| \leq 2^{N(H(X) - \epsilon)}$$

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Let's look at what this says about $P(x \in S_{\delta})$ by writing

$$P(x \in S_{\delta}) = P(x \in S_{\delta} \cap T_{N\beta}) + P(x \in S_{\delta} \cap \overline{T_{N\beta}})$$
$$\leq |S_{\delta}| 2^{-N(H-\beta)} + P(x \in \overline{T_{N\beta}})$$

since every $x \in T_{N\beta}$ has $P(x) \leq 2^{-N(H-\beta)}$ and $S_{\delta} \cap \overline{T_{N\beta}} \subset \overline{T_{N\beta}}$.

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$$P(x \in S_{\delta}) \leq 2^{-N(\epsilon - \beta)} + P(x \in \overline{T_{N\beta}}) \to 0$$
 as $N \to \infty$

since $P(x \in T_{N\beta}) \rightarrow 1$.

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since $P(x \in T_{N\beta}) \rightarrow 1$. But $P(x \in S_{\delta}) \ge 1 - \delta$, by defn. Contradiction

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$$\frac{1}{N}H_{\delta}\left(X^{N}\right)-H\right|<\epsilon.$$

If you want to uniformly code blocks of N symbols drawn i.i.d. from X

- If you use more than NH(X) bits per block you can do so without almost no loss of information as $N \to \infty$
- If you use less than NH(X) bits per block you will almost certainly lose information as $N \to \infty$