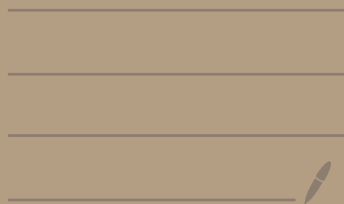


# Information Theory & Coding

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Dec 7, 2020



## Wrapping up polar codes

- scene: given a channel  $w$ , the polar transform

applied  $t$ -times:

- synthesizes  $2^t$  channels  $\{w^s: s \in \{0, 1\}^t\}$  from  $2^t$  uses of the "real" channel  $w$ .
- for any fixed  $\epsilon > 0$ ,  
fraction of  $\epsilon$ -good channels  $\rightarrow I(w)$   
~~tree~~

• to convert this to a code seems reasonable, but we need to show something stronger about the  $\epsilon$ -good channels: i.e., most of these  $\epsilon$ -good channels should also be  $\epsilon_t$ -good

$$\text{with } \epsilon_t \ll \frac{1}{2^t} \Rightarrow P_\epsilon(\text{construction}) \rightarrow 0 \text{ as } t \rightarrow \infty$$

for this end, we defined the notion of  $\epsilon$ -unfaded, &  $\epsilon$ -lucky channels.

$\epsilon$ -untainted:  $w^{st}$  is  $\epsilon$ -tainted if

$\exists i \in [st, t)$  s.t.  $w^{s^i}$  is  $\epsilon$ -ugly

we show fraction of  $\epsilon$ -tainted channels among

$$\{w^s : s \in \{t, -\}^t\} \rightarrow 0 \text{ as } t \rightarrow \infty$$

$\epsilon$ -lucky:  $w^{st}$  is  $\epsilon$ -lucky if

$$\# \text{ of } - \text{ signs in } st < \left(\frac{1}{2} - \epsilon\right)t$$

$\Rightarrow$  fraction of unlucky channels  $\rightarrow 0$  as  $t \rightarrow \infty$

$\Rightarrow$  the fraction of  $\epsilon$ -good,  $\epsilon$ -lucky,  $\epsilon$ -untainted channels

$$\text{among } \{w^{st} : st \in \{t, -\}^t\} \rightarrow I(\omega) \text{ as } t \rightarrow \infty$$

Idea: use these channels to communicate data, or the other way, send fixed known bits.

We will now show (for the BEC case) that

$\epsilon$ -good, lucky, untainted channels are in fact

$$\text{good with } \epsilon_t \ll \frac{1}{2}t.$$

$$p(s^{i+1}) = \begin{cases} p(s^i)^2 & s_{i+1} = + \\ 2p(s^i) - p(s^i)^2 & s_{i+1} = - \end{cases}$$

$$\leq \begin{cases} p(s^i)^2 & + \\ 2p(s^i) & - \end{cases}$$

$$p(s^{i+1}) \leq \begin{cases} p(s^i)^2 & + \\ p(s^i) \varepsilon^{1/\log \varepsilon} & - \end{cases} \quad \begin{array}{l} z = \varepsilon^x \\ \log z = x \log \varepsilon \end{array}$$

$$\leq \begin{cases} p(s^i)^2 & + \\ p(s^i) p(s^i)^{1/\log \varepsilon} & - \end{cases}$$

$\omega^{st}$  is  $\varepsilon$ -good  
- lucky  
- unfortunate

$$\underline{p(s^i) \leq \varepsilon}$$

$$\log p(s^{i+1}) \leq (\log p(s^i)) \times \begin{cases} 2 & + \\ 1 + \frac{1}{\log \varepsilon} & - \end{cases}$$

$$\log \log \frac{1}{p(s^{i+1})} \geq \log \log \frac{1}{p(s^i)} + \begin{cases} 1 & + \\ -\varepsilon'' & - \end{cases}$$

$$-\varepsilon'' = \log(1 - \varepsilon')$$

$$\log \log \frac{1}{p(s^t)} \geq \log \log \frac{1}{p(s^{t_0})} + \# \{t' \text{ in } (s_{t_0}, s_t)\} \\ \rightarrow \varepsilon'' \{ \# - 's \text{ " } \}$$

Since  $w^{st}$  is  $\epsilon$ -lucky

$$\text{the \# of signs in } \sum_{\sqrt{t}}^s \dots s_t \leq (1+\epsilon) \frac{t}{2}$$

$$+ \dots \geq t - \sqrt{t} - (1+\epsilon) \frac{t}{2}$$

$$\log_{\log} \frac{1}{p(st)} \geq \log_{\log} \frac{1}{p(s^{\sqrt{t}})} + \left( t - \sqrt{t} - (1+\epsilon) \frac{t}{2} \right) - \epsilon'' (1+\epsilon) \frac{t}{2}$$

$$= \frac{t}{2} (1 - \epsilon''')$$

So an  $\epsilon$ -good, lucky, untruncated channel  $w^s$  has

$$\log_{\log} \frac{1}{p(st)} \geq \log_{\log} \frac{1}{\epsilon} + \frac{t}{2} (1 - \epsilon''')$$

$$\geq \frac{t}{2} (1 - \epsilon''') \quad \text{if } \epsilon \text{ small enough}$$

$$p(st) \leq 2^{-\frac{t}{2} (1 - \epsilon''')} \approx 2^{-t}$$

We conclude that the error probability of a code constructed as above

$$\leq 2^t \cdot 2^{-2^{\frac{t}{2}(1-\epsilon^{1/n})}} = 2^{-\frac{2^{\frac{t}{2}(1-\epsilon^{1/n})}}{2^t}} \approx \sqrt{n}$$

$$2^t = n = \text{blocklength}$$

So: we can design polar codes with

- rates up to  $I(W)$
  - enc/dec complexity  $n \log_2 n$
  - $p(\text{error}) \approx 2^{-\sqrt{n}}$
- as  $t = \log_2 n$  gets large.

We gave the proof for  $W = \text{BEC}()$ , but the

condition holds for any binary-input channels,

can be generalized to non-binary inputs, &

non-uniform input distributions.

## Back to Source coding $\rightarrow$ Lossy Compression

Recall: we had discussed "exact" (= "lossless") source coding at the beginning of the semester

$$c: \mathcal{U}^n \rightarrow \{0,1\}^*$$

We may want to give up on "exactness" & tolerate some loss, in the hope of improving efficiency. (i.e. fewer bits/letter).

Question: what <sup>are</sup> the fundamental limits of the tradeoff between quality (= fidelity) & efficiency (= bit-rate)?

We will see "some" answers to this question.

Let us consider the following set-up:

$U_1, U_2, U_3, \dots$  — i.i.d.  $\sim$   $P_{\text{src}}$  source.

a lossy source encoder/decoder:

$$\text{enc}: \mathcal{U}^n \rightarrow \{1, \dots, M\} \equiv \log_2 M \text{ bit description of } n \text{ source letters}$$

(rate =  $\frac{1}{n} \log_2 M$ )

$$\text{dec}: \{1, \dots, M\} \rightarrow \mathcal{V}^n$$

$\{1, \dots, M\}$  is  
descriptors

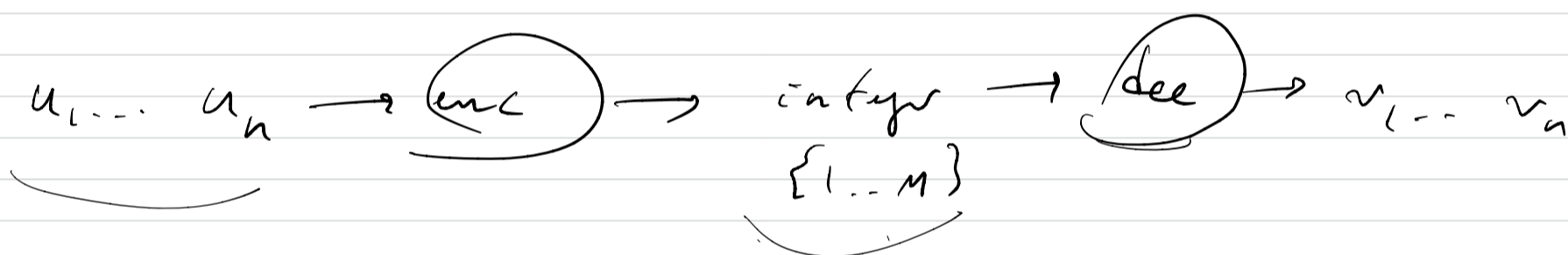
$\mathcal{U}$ : source alphabet

$\mathcal{V}$ : reproduction alphabet

We also have a "distortion measure"  $d$ ,

$$d: \mathcal{U} \times \mathcal{V} \rightarrow \mathbb{R} \quad d(u, v) \text{ is the cost (distortion) (in fidelity)}$$

$\gamma$  represents  $u$  by  $v$ .



$$\text{distortion} = \frac{1}{n} \sum_{i=1}^n d(u_i, v_i)$$

examples  $\mathcal{U} = \mathcal{V} = \{0, 1\}$      $d(u, v) = \mathbb{1}\{u \neq v\}$  ←

$\mathcal{U} = \mathcal{V} = \mathbb{R}$      $d(u, v) = \underline{(u - v)^2}$

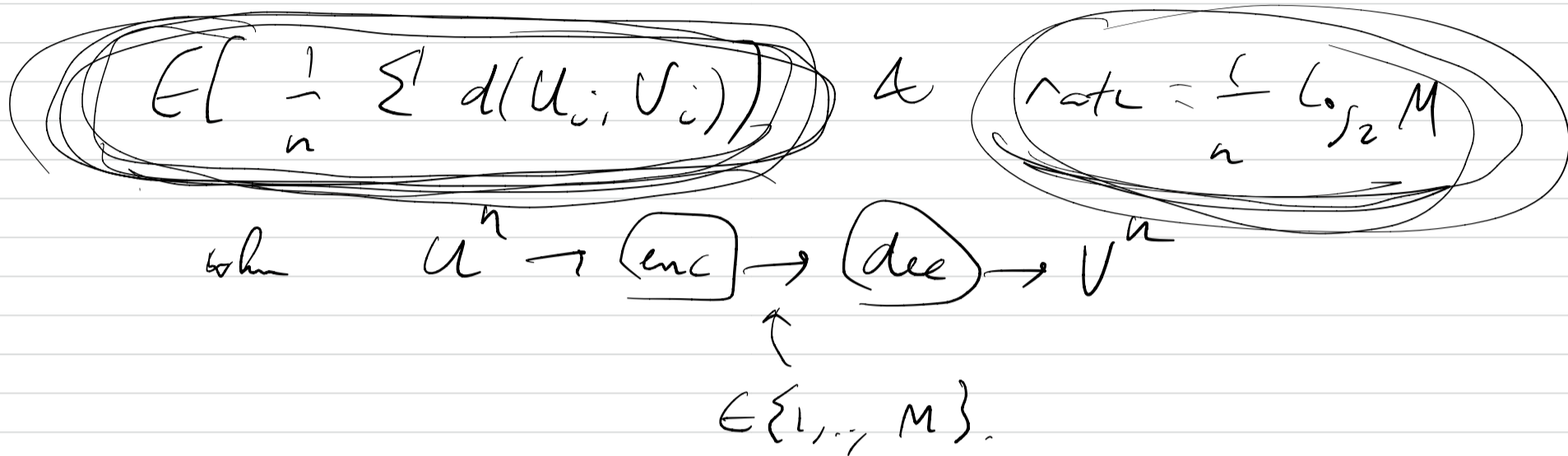
$\mathcal{U} = \{0, 1\}$      $\mathcal{V} = \{0, 1, ?\}$      $d(0, 0) = 0 = d(1, 1)$  //  
 $d(0, 1) = 1 = d(1, 0)$  //  
 $d(0, ?) = 1 = d(1, ?)$



distortion:  $\frac{1}{n} \sum d(u_i, v_i)$  becomes a Random

variable when the input to the enc is  $U_1 \dots U_n$

we will study the trade-off between



The prototypical result we will prove is of the following kind:

Thm: given  $U_1, U_2, \dots$ , i.i.d. or  $P_{U^n}$

given a reproduction alphabet  $V$  and

distortion measure  $d: U \times V \rightarrow \mathbb{R}$ .

Compute  $\min_{P_{V|U}} I(U; V) \stackrel{\Delta}{=} R(D)$

$E[d(U, V)] \equiv D$

$\min_{P_{V|U}} E[d(U, V)] \leq D \leq \max_{P_{V|U}} E[d(U, V)]$

$P_{V|U} \quad \uparrow \quad P_{V|U}$

Then any system (i.e. enc/dec)



$E(\text{distortion}) = D$  has rate  $\geq R(D)$ .

Before the proof some examples of computation:

Ex:  $U \in \{0,1\}$  Bern  $(\frac{1}{2})$   $P(u=0) = \frac{1}{2}$   
 $P(u=1) = \frac{1}{2}$

given  $V = \{0,1\}$   $d(u,v) = \mathbb{1}\{u \neq v\}$ .

$0 \leq D \leq 1$ , how do we compute

$$\min \left\{ I(U;V) : P_V(u) \text{ with } E(d(U,V)) = D \right\}$$

to this end, for such a  $V$ :

$$I(U;V) = H(U) - H(\underline{U|V})$$

$$= 1 - H(\underline{U \oplus V | V})$$

$$\geq 1 - H(U \oplus V)$$

$$\left\{ \begin{array}{l} 0 \text{ if } u=v \\ 1 \text{ if } u \neq v \end{array} \right\}$$

$$\text{hence } U \oplus V = \begin{cases} 1 & \text{w.p. } D \\ 0 & \text{w.p. } 1-D \end{cases}$$

$$\Rightarrow H(U \oplus V) = h_2(D)$$

$$I(U; V) \geq \underline{1 - h_2(D)}$$

$$\Rightarrow R(D) \geq 1 - h_2(D)$$

now observe:

$$\frac{1}{2} \text{ } 0 \text{ } a \quad \xrightarrow{\quad} \text{ } \text{ } \frac{1}{2}$$

$D \setminus \setminus$

$$\frac{1}{2} \text{ } 1 \text{ } \cdot \quad \xrightarrow{\quad} \text{ } \text{ } \frac{1}{2}$$

$D / \setminus$

$$U \quad \text{BSC}(D) \quad V$$

$$p(u, v) = \begin{cases} \frac{1}{2} D & \text{if } u \neq v \\ \frac{1}{2} (1-D) & \text{if } u = v \end{cases}$$

$U \oplus V$  = indicator of "flip" -  $\mathbb{1}_y$  of  $U$ .

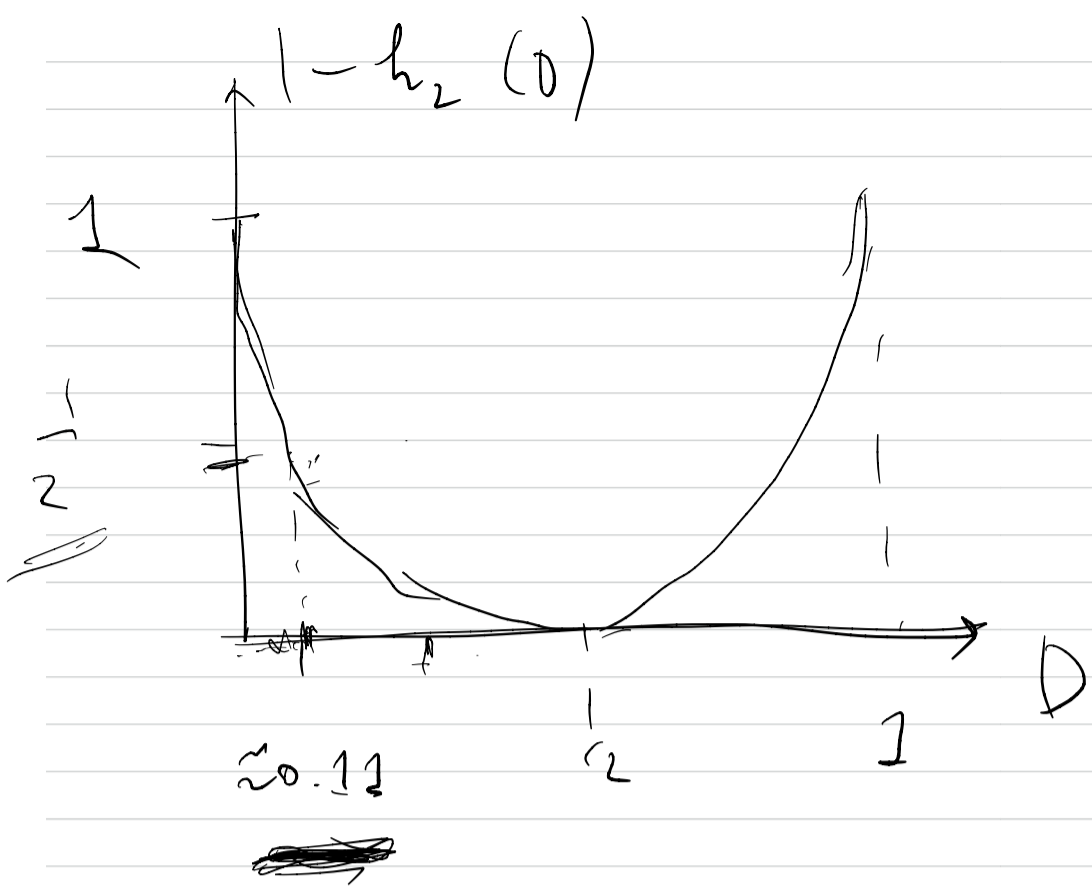
Because of the symmetry of  $p(u, v)$  in  $u \leftrightarrow v$ .

$$U \oplus V \text{ is index of } V$$

$$\Rightarrow H(U \oplus V | V) = H(U \oplus V), \text{ which makes the}$$

lower bound to be equality in  $I(U; V) \geq 1 - h_2(D)$ .

$$\Rightarrow R(D) = 1 - h_2(D)$$



We will also show:

Theorem: given  $P_u$ , iid  $U, V$ ,

$\mathcal{V}$ ,  $d(n, N)$ , ...  $R(D)$  just as in

the theorem above, given  $\epsilon > 0$ . There

exists enc, dec. s.t

$$U^n \rightarrow \text{enc} \rightarrow \text{dec} \rightarrow V^n$$

①. rate  $\leq R(D) + \epsilon$ .

②  $|E(\text{distortion}) - D| < \epsilon$ .

(Theorem: proof of these two complementary theorems.)