

Privacy amplification, lossy compression, and their duality to channel coding

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arXiv:1708.05685

Overview

I. Information theory

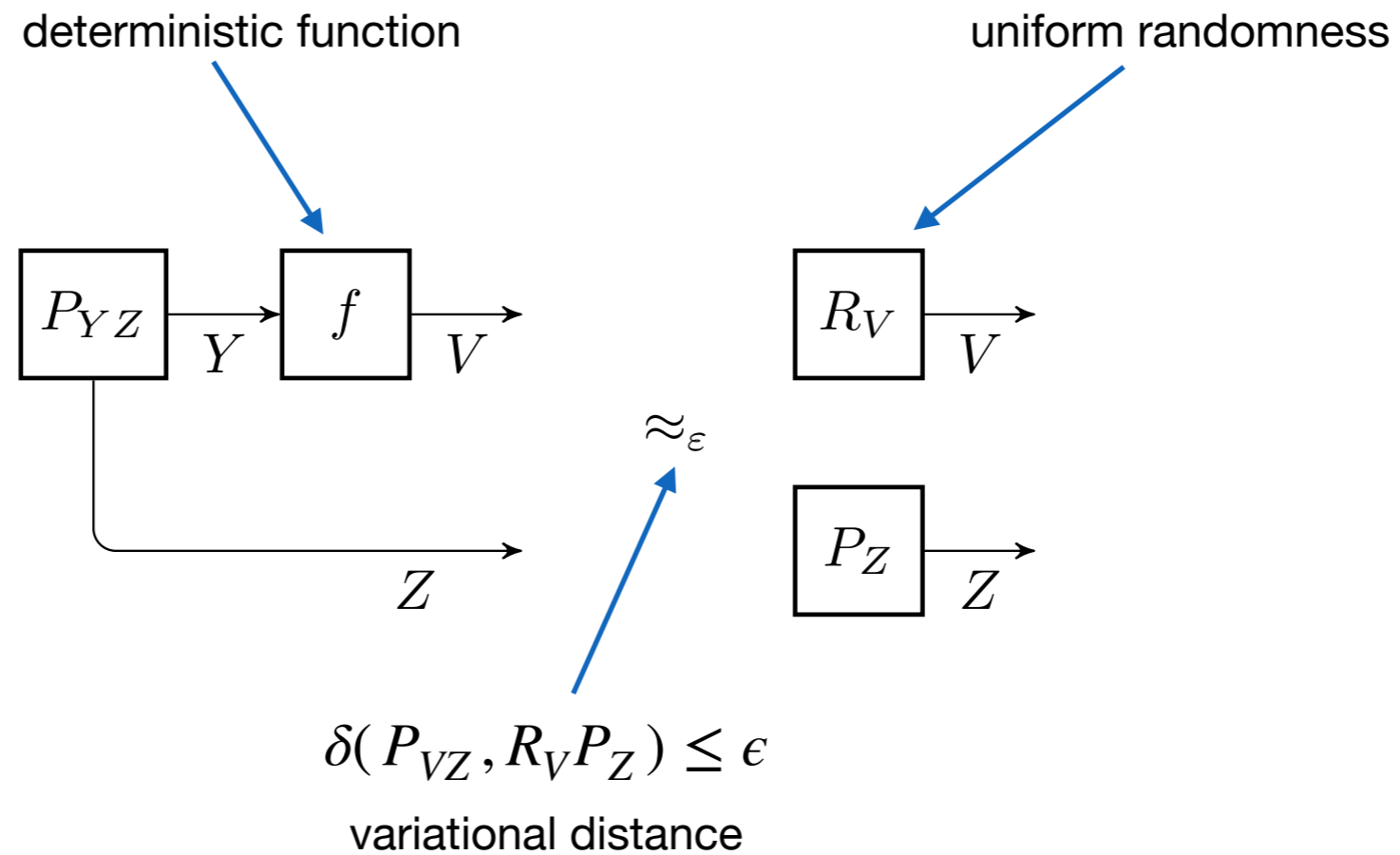
- hypothesis testing converse for privacy amplification against classical side information

II. Coding theory

- how to use channel codes for lossy compression

Information theory

Privacy amplification



$$K_\epsilon(Y|Z)_P := \max |V| \text{ such that } \epsilon\text{-good } f \text{ exists}$$

Guessing probability converse

Watanabe/Hayashi ISIT 2013

$$\frac{1}{K_\epsilon(Y|Z)_P} \geq P_{\text{guess}}^\epsilon(Y|Z)_P$$

Consider worst case (for Alice) guessing probability (for Eve)

$$P_{\text{guess}}(Y|Z)_P := \max_{y,z} P_{Y|Z=z}(y) \quad P_{\text{guess}}^\epsilon(Y|Z)_P := \min_{Q \approx_\epsilon P} \max_{y,z} \frac{Q_{YZ}(y,z)}{P_Z(z)}$$

$$P_{\text{guess}}^\epsilon(f(Y)|Z) \geq P_{\text{guess}}^\epsilon(Y|Z)$$

Difficult to compute for finite-blocklength due to Q minimization;
relax to information spectrum quantity

Guessing probability LP formulation

$$P_{\text{guess}}^\epsilon(Y|Z)_P = \underset{\lambda, Q, T}{\text{minimum}} \quad \lambda$$

such that

$$\lambda \mathbb{1}_Y P_Z \geq Q_{YZ}$$
$$T_{YZ} \geq P_{YZ} - Q_{YZ}$$
$$\text{Tr}[T_{YZ}] \leq \epsilon$$
$$\text{Tr}[Q_{YZ}] = 1$$
$$\lambda, T_{YZ}, Q_{YZ} \geq 0$$

Note: by normalization of Q, we have $\lambda |Y| \geq 1$

Guessing bound is never looser than the trivial bound $K_\epsilon(Y|Z)_P \leq |Y|$

Hypothesis-testing converse

R, arXiv:1708.05685

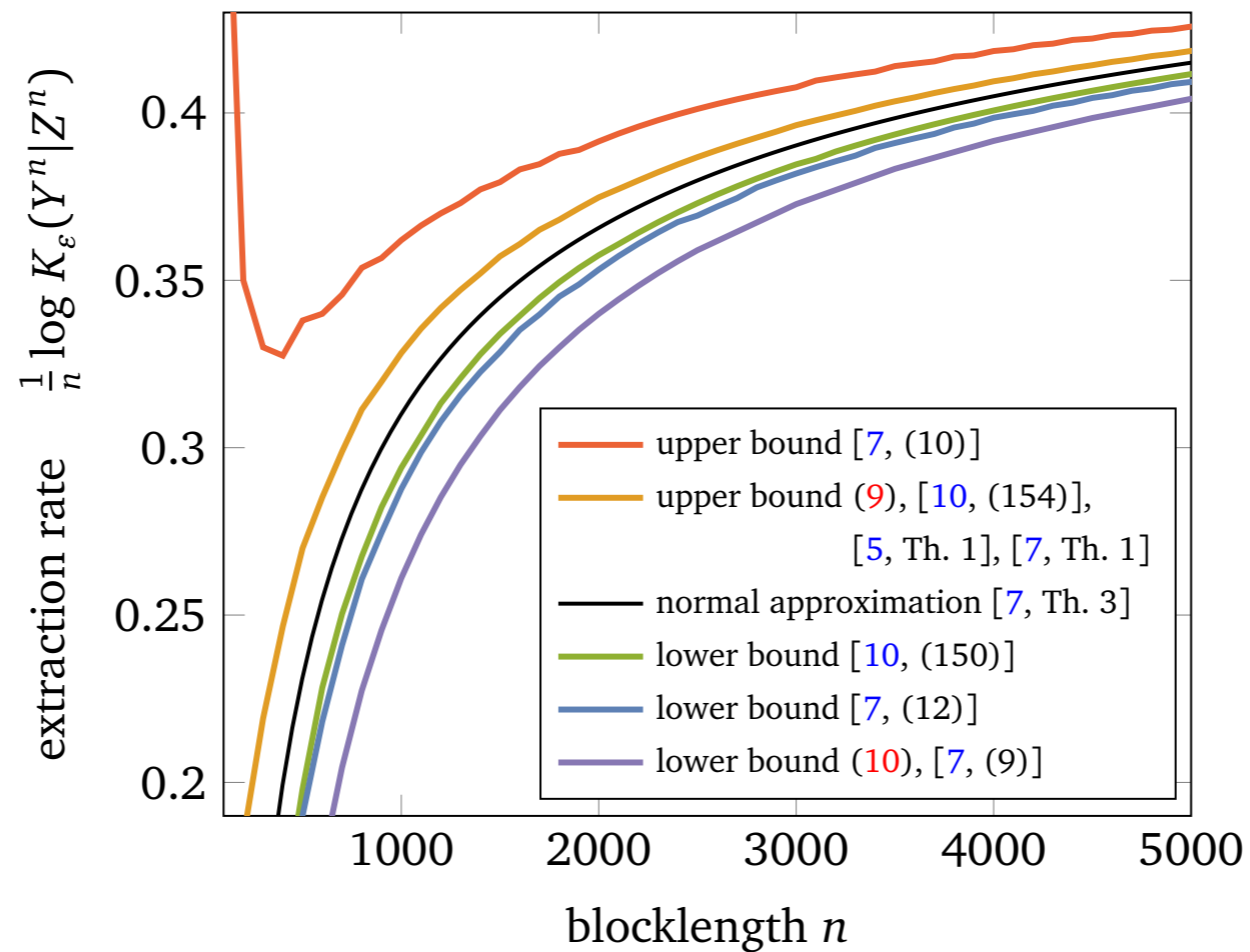
$$K_\epsilon(Y|Z)_P \leq \min_{\eta \in [0, 1-\epsilon]} \frac{1}{\eta} \beta_{\epsilon+\eta}(P_{YZ}, 1_Y P_Z)$$

- ▶ $\beta_\alpha(P, Q) := \min\{\text{Tr}[\Lambda Q] : \text{Tr}[\Lambda P] \geq \alpha, 0 \leq \Lambda \leq 1\}$
- ▶ $\alpha - \delta(P, Q) \leq \beta_\alpha(P, Q)$
- ▶ $\beta_\alpha(P_{f(Y)Z}, 1_{f(Y)} P_Z) \leq \beta_\alpha(P_{YZ}, 1_Y P_Z)$



bound does not hold for quantum Z

Finite blocklength example



$$\epsilon = 1/10^{10}$$

$$Z = Y + X$$

$$X = \text{Ber}(0.11)$$

311 ± 17 at blocklength 1000

Relation to guessing bound

$$K_\epsilon(Y|Z)_P \leq \min_{\eta \in [0, 1-\epsilon]} \frac{1}{\eta} \beta_{\epsilon+\eta}(P_{YZ}, 1_Y P_Z) \iff \epsilon \geq E_{Y|K_\epsilon}(P_{YZ}, R_Y P_Z)$$

Yang, Schaefer, Poor
IEEE TIT 2019

$$E_\gamma(P, Q) := \max\{\text{Tr}[\Lambda P] - \gamma \text{Tr}[\Lambda Q] : 0 \leq \Lambda \leq 1\}$$

Using properties of E_γ divergence from Liu, Cuff, Verdú (IEEE TIT 2017), we obtain

$$\frac{1}{K_\epsilon(Y|Z)_P} \geq \hat{P}_{\text{guess}}^\epsilon(Y|Z)_P \quad \hat{P}_{\text{guess}}^\epsilon(Y|Z)_P = \underset{\lambda, Q, T}{\text{minimum}} \lambda$$

such that

$$\begin{aligned} \lambda 1_Y P_Z &\geq Q_{YZ} \\ T_{YZ} &\geq P_{YZ} - Q_{YZ} \\ \text{Tr}[T_{YZ}] &\leq \epsilon \\ \text{Tr}[Q_{YZ}] &= 1 \\ \lambda, T_{YZ}, Q_{YZ} &\geq 0 \end{aligned}$$

Hence the HT bound is a relaxation
of the guessing bound

Equivalence!

It can happen that $\hat{P}_{\text{guess}}^\epsilon(Y|Z)_P < \frac{1}{|Y|}$

meaning the HT bound can be looser than the trivial bound (!)

$$\hat{P}_{\text{guess}}^\epsilon(Y|Z)_P = \underset{\lambda, Q, T}{\text{minimum}} \lambda$$

such that

$$\left. \begin{array}{l} \lambda \mathbb{1}_Y P_Z \geq Q_{YZ} \\ Q_{YZ} \geq P_{YZ} - T_{YZ} \\ \text{Tr}[T_{YZ}] \leq \epsilon \\ \lambda, T_{YZ}, Q_{YZ} \geq 0 \end{array} \right\} \Rightarrow 1 - \epsilon \leq \text{Tr}[Q_{YZ}] \leq \lambda |Y|$$

Therefore, whenever HT is nontrivial
the HT and guessing bounds are equivalent!

More equivalence: Achievability

Recent approach from quantum information: partial smoothing

$$P_{\text{guess}}^\epsilon(Y|\dot{Z})_P = \underset{\lambda, Q, T}{\text{minimum}} \lambda$$

such that

$$\lambda \mathbb{1}_Y P_Z \geq Q_{YZ}$$
$$T_{YZ} \geq P_{YZ} - Q_{YZ}$$
$$\text{Tr}[T_{YZ}] \leq \epsilon$$
$$\text{Tr}[Q_{YZ}] = 1$$
$$Q_Z \leq P_Z$$
$$\lambda, T_{YZ}, Q_{YZ} \geq 0$$

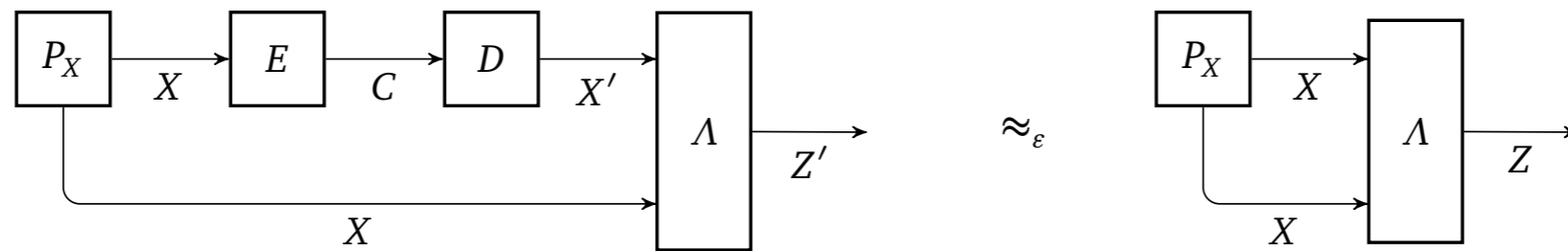
Anshu, Berta,
Jain, and Tomamichel
arXiv:1807.05630

Can also obtain achievability bounds using the collision entropy

But partial smoothing = global smoothing classically,
therefore Anshu et al.'s bound = Yang et al.'s bound

Coding theory

Lossy compression



- * Compress X so that average distortion of the reconstruction X' is small.
- * Usual examples:
 - ❖ Gaussian source: recover up to small mean-squared error
 - ❖ Uniform discrete source: recover up to Hamming distortion
(fraction of incorrect bits)

Rate-distortion function

$$R(\bar{d}) = \min_{P_{Y|X}: \langle d(X,Y) \rangle \leq \bar{d}} I(X : Y)$$

A “curious duality”

Erasure quantization BEQ(e):

Martinian & Yedidia Allerton 2004

\mathcal{X}	0	1	?
P_X	$\frac{1}{2}(1-e)$	$\frac{1}{2}(1-e)$	e

$$d(x, x') = \begin{cases} 0 & x = ?, x' = ?, x = x' \\ 1 & \text{else} \end{cases}$$

$$R(\bar{d}) = (1-e)(1 - h_2(\frac{\bar{d}}{1-e}))$$

Kostina & Verdú IEEE TIT 2012

- * Consider zero distortion
- * Quantize using linear code: Assign 0/1 to ?'s to get a codeword
- * M&Y:

If linear codes C_n achieve the capacity $1-e$ for BEC(e) under optimal decoding, then their duals C_n^d achieve $R(0)$ for BEQ(1-e) under optimal quantization.

“The statement and proof of the two preceding results contain a curious duality between erased/known symbols in source coding and known/erased symbols in channel coding.”

This curious duality is quantum!

Compression via privacy amplification

1. Pick a channel achieving R . This gives P_{XY} .
2. Find (linear) f for PA of Y relative to X .
3. Extend to reversible $g:Y \rightarrow (V,T)$. This gives P_{TVX} .
4. Quantizer is channel $P_{T|VX}$.
Dequantizer is g^{-1} .
5. Both use common randomness V .
Derandomize if desired.
6. Size of the code is $|T|=|Y|/|V|$

Similar to, but more direct than:
Muramatsu, IEEE TIT 2014,
Yassaee, Aref, Gohari, IEEE TIT 2014

Why does it work?

- * Input to quantizer is: $R_V P_X \approx_\epsilon P_{VX}$
- * Quantizer produces: $\mathcal{Q}(R_V P_X) \approx_\epsilon P_{TVX}$
- * Dequantizer gives: $\mathcal{D} \circ \mathcal{Q}(R_V P_X) \approx_\epsilon P_{YX}$

$f(x^n)$ = syndromes of C ,

$g^{-1}(t,v)$ = t -th codeword,
offset to v -th coset

Privacy amplification via channel coding

* P_{XY} also defines the channel $P_{X|Y}$.

* Get extractor for $Y | X$ from channel code for dual of $P_{X|Y}$

(M, ϵ) code for $P_{X|Y}^\perp \iff (M, \sqrt{2\epsilon})$ extractor for $Y | X$ R IEEE TIT 2018

(M, ϵ) code for $P_{X|Y}^\perp \implies (|Y|/M, \sqrt{2\epsilon})$ quantizer for P_{XY}

For i.i.d. X^n , achieve a rate of $\frac{1}{n} \log \frac{|Y|}{M} \rightarrow 1 - C(P_{X|Y}^\perp)$

If capacity optimizer is uniform, then $C(P_{X|Y}^\perp) = 1 - I(X : Y)$

❖ Hamming distortion

❖ BEQ(e)

Therefore, we recover the optimal quantizer rate!

The “curious duality” is a quantum duality.

Dual of uniform bit compression: pure state channel

Outlook

I. Information theory

- ▶ Still missing good PA bounds for quantum adversaries... (Could try duality.)

II. Coding theory

- ▶ Can we go from lossy compression to channel coding? (Does compression always effectively implement PA?)