

Variable-Length Feedback Codes over Known and Unknown Channels

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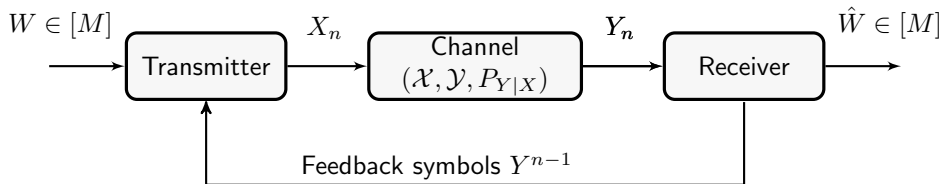
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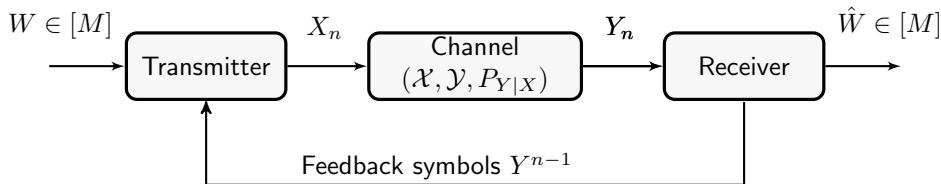


Variable-length feedback (VLF) codes



- Decoding occurs at a random stopping time $\tau \in \mathbb{N}$ (Burnashev '76)
 - ▶ Burnashev proved that the optimal error exponent is $\lim_{\epsilon \rightarrow 0} \frac{-\log \epsilon}{\mathbb{E}[\tau]} = C_1 \left(1 - \frac{R}{C}\right)$
- Polyanskiy et al. '11 showed an achievability bound for fixed $\epsilon \in (0, 1)$
 - ▶ Their scheme employs only stop-feedback

Variable-length feedback (VLF) codes



- An (N, M, ϵ) -VLF code consists of a sequence of encoders f_n , a stopping time τ , and a decoder g :

$$X_n = f_n(W, Y^{n-1}) \quad W \sim \text{Unif}[M]$$

$$\hat{W} = g(Y^\tau) \quad \tau : \text{stopping time of filtration } \sigma\{Y^n\}$$

$$\mathbb{P}[W \neq \hat{W}] \leq \epsilon \quad \text{average error probability}$$

$$\mathbb{E}[\tau] \leq N \quad \text{average decoding time}$$

- $M^*(N, \epsilon) = \max\{M : \exists (N, M, \epsilon)\text{-VLF code}\}$

- Information density:

$$i(x^n; y^n) = \sum_{i=1}^n \log \frac{P_{Y|X}(y_i|x_i)}{P_Y(y_i)}$$

- Mutual information:

$$I(P_X, P_{Y|X}) = \mathbb{E}[i(X; Y)] = \sum_{x,y} P_X(x) P_{Y|X}(y|x) \log \frac{P_{Y|X}(y|x)}{P_Y(y)}$$

- Capacity:

$$C = \max_{P_X} I(P_X, P_{Y|X})$$

- KL divergence between the two most distinguishable inputs:

$$C_1 = \max_{x_A, x_R} D(P_{Y|X=x_A} \| P_{Y|X=x_R})$$

- In fixed-length channel coding (decoding is done at a fixed time n):

- ① Shannon (1949) shows

$$\log M^*(n, \epsilon) = nC + o(n).$$

- ② Strassen (1961) and Polyanskiy et al. (2010) show

$$\log M^*(n, \epsilon) = nC - \sqrt{nV}Q^{-1}(\epsilon) + O(\log n)$$

where $V = \text{Var} [i(X; Y)]$ and $Q^{-1}(\cdot)$ is complementary Gaussian CDF.

- In variable-length channel coding (decoding is done at a random time τ with $\mathbb{E}[\tau] \leq N$):

① Polyanskiy et al. (2011) show

$$\frac{NC}{1-\epsilon} - \log N + O(1) \leq \log M^*(N, \epsilon) \leq \frac{NC}{1-\epsilon} + O(1)$$

- ▶ The first-order term is larger by a multiplicative factor of $\frac{1}{1-\epsilon}$
- ▶ Faster convergence to the first-order term since the second-order term is $O(\log N)$ instead of $O(\sqrt{N})$

- We prove a novel achievability bound in the fixed- ϵ regime.
Our result improves the second-order term from

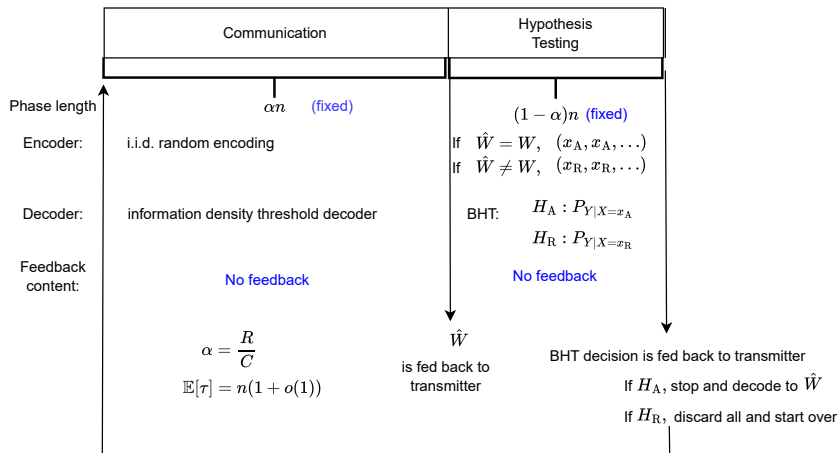
$$-\log N \quad \text{to} \quad -\frac{C}{C_1} \log N$$

($C < C_1$ holds for all nontrivial DMCs)

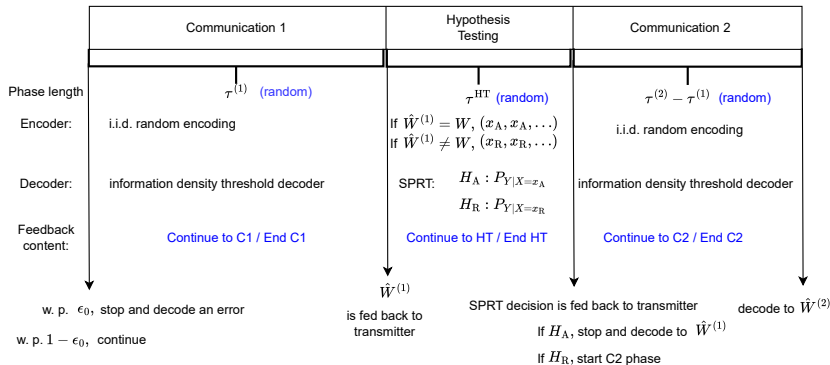
- Our code is a refinement of the Yamamoto–Itoh scheme.
- We universalize our code for a scenario where the channel is unknown.

Original Yamamoto–Itoh Scheme

- Phases go indefinitely until decoding occurs.

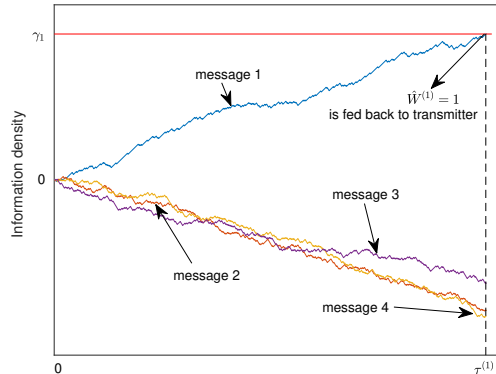


- Consists of 3 phases: C1, HT, and C2.



- Message W is uniformly distributed on $[M] = \{1, \dots, M\}$.
- **Encoder:** The transmitter transmits the codeword associated with W symbol by symbol.
- $\mathbf{c}(W) \sim P_X^\infty$
infinite-length codeword corresponding to W
 $\mathbf{c}^n(W) =$ first n symbols of $\mathbf{c}(W)$

- **Decoder:**



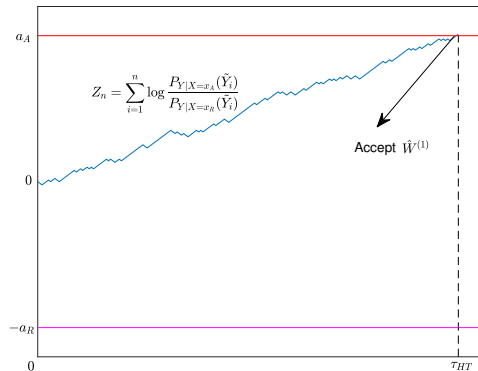
$$\tau^{(1)} = \inf\{n \geq 1: \max_{m \in [M]} \iota(\mathbf{c}^n(m); Y^n) > \gamma_1\}$$

- Upon receiving $\hat{W}^{(1)}$, if $W = \hat{W}^{(1)}$ (correct estimate), the transmitter transmits (x_A, x_A, \dots) . If $W \neq \hat{W}^{(1)}$, it transmits (x_R, x_R, \dots) , where

$$(x_A, x_R) = \arg \max_{x_A, x_R} D(P_{Y|X=x_A} \| P_{Y|X=x_R})$$

The receiver receives $(\tilde{Y}_1, \tilde{Y}_2, \dots)$.

- Decoder: SPRT**



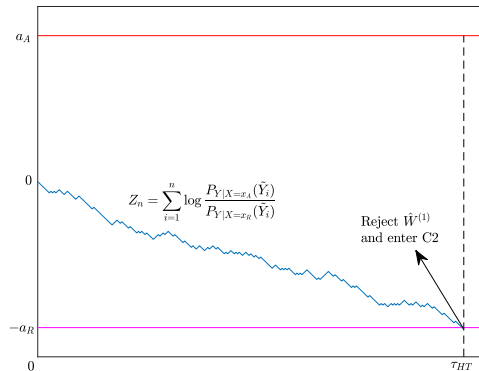
$$\tau^{HT} = \inf \left\{ n \geq 1 : \sum_{i=1}^n \log \frac{P_{Y|X=x_A}(\tilde{Y}_i)}{P_{Y|X=x_R}(\tilde{Y}_i)} \in [-a_R, a_A] \right\}$$

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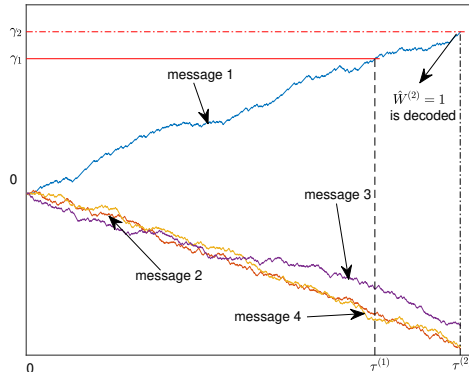
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- **Encoder:** The transmitter continues to transmit the symbols from $\mathbf{c}(W)$.
- $\mathbf{c}_{\tau^{(1)}+1}(W), \mathbf{c}_{\tau^{(1)}+2}(W), \dots$ are transmitted until the decoder makes a decision

- **Decoder:**



$$\tau^{(2)} = \inf\{n \geq 1: \max_{m \in [M]} \iota(\mathbf{c}^n(m); Y^n) > \gamma_2\}$$

- To improve the performance, we employ Polyanskiy et al.'s *stop-at-time-zero* strategy:

With probability ϵ_0 , decode to an arbitrary message at time $\tau = 0$

With probability $1 - \epsilon_0$, use the code described above

- Overall error probability

$$\epsilon \leq (1 - \epsilon_0)\epsilon' + \epsilon_0$$

- Overall average decoding time

$$N = (1 - \epsilon_0)N',$$

where N' and ϵ' are the average decoding time and average error probability of the Yamamoto–Itoh code.

Theorem 1

There exists an (N, M, ϵ) -VLF code with

$$N \leq (1 - \epsilon_0)N' \quad \text{and} \quad \epsilon \leq \epsilon_0 + (1 - \epsilon_0)\epsilon'$$

where

$$\begin{aligned} \epsilon' &= (M - 1) \exp\{-(\gamma_1 + a_A)\} + (M - 1) \exp\{-\gamma_2\} \\ N' &= \frac{\gamma_1 + b}{C} + ((M - 1) \exp\{-\gamma_1\} + \exp\{-a_R\}) \frac{\gamma_2 - \gamma_1 + b}{C} + \frac{a_A + b_A}{D(P_{Y|X=x_A} \| P_{Y|X=x_R})} \\ &\quad + (M - 1) \exp\{-\gamma_1\} \frac{a_R + b_R}{D(P_{Y|X=x_R} \| P_{Y|X=x_A})} \end{aligned}$$

b, b_A, b_R are constants, and $\epsilon_0, \gamma_1, \gamma_2, a_A$, and a_R are the parameters of our code design.

Theorem 1

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- Upper bound on \mathbb{P} [Error at the end of HT]

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- Upper bound on $\mathbb{P}[\text{Error at the end of C2}]$

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- Upper bound on $\mathbb{E}[\tau^{(1)}]$

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- Upper bound on $\mathbb{E} [\tau^{(2)} - \tau^{(1)}]$

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- Upper bound on $\mathbb{E}[\tau^{\text{HT}}]$

Theorem 2

Assume that $C > 0$ and $C_1 < \infty$. Then,

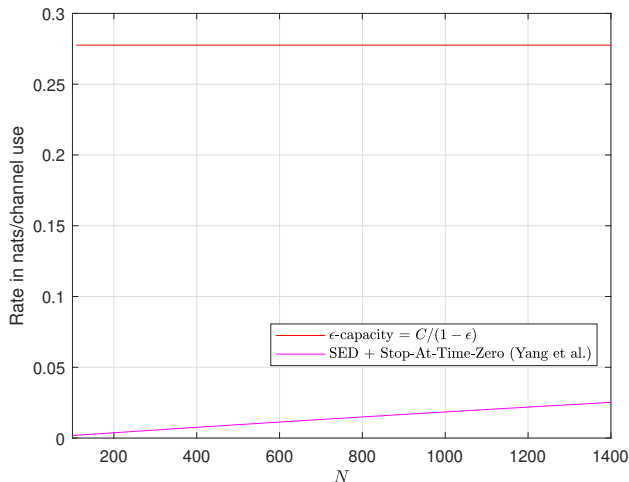
$$\log M^*(N, \epsilon) \geq \frac{NC}{1 - \epsilon} - \frac{C}{C_1} \log N - \log \log N + O(1)$$

- It improves the best second-order term in the literature from $-\log N$ to $-\frac{C}{C_1} \log N$
- Upper bound:

$$\log M^*(N, \epsilon) \leq \frac{NC}{1 - \epsilon} + \underbrace{\frac{-\epsilon \log(\epsilon) - (1 - \epsilon) \log(1 - \epsilon)}{1 - \epsilon}}_{O(1)}$$

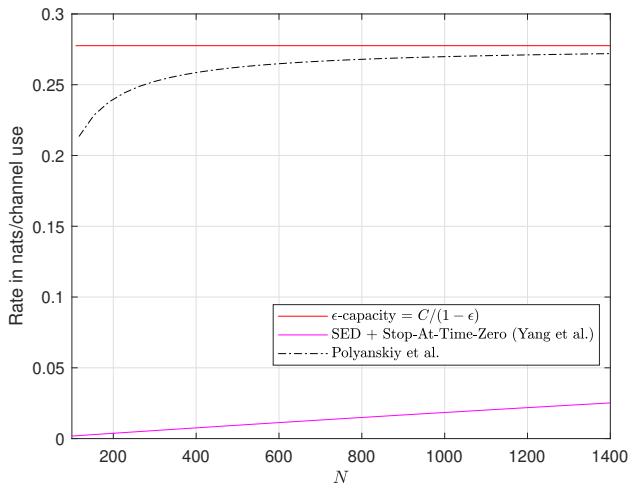
- The gap from the best upper bound is $O(\log N)$.

Channel: Cascade of BSC(0.11) and BEC(0.2)



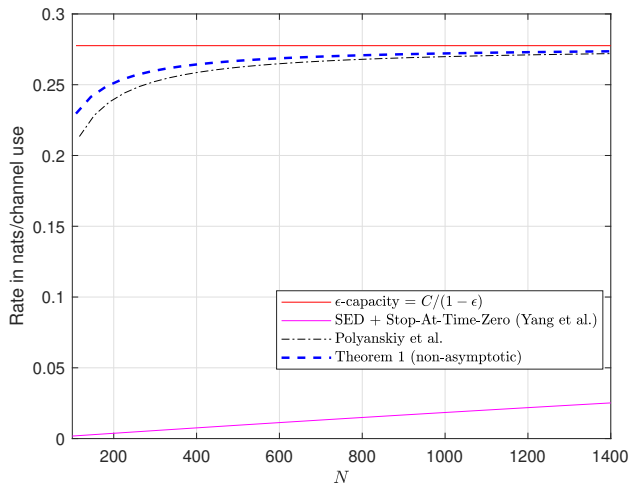
- The non-asymptotic bound for SED code is far from ϵ -capacity (it asymptotically achieves ϵ -capacity)

Channel: Cascade of BSC(0.11) and BEC(0.2)



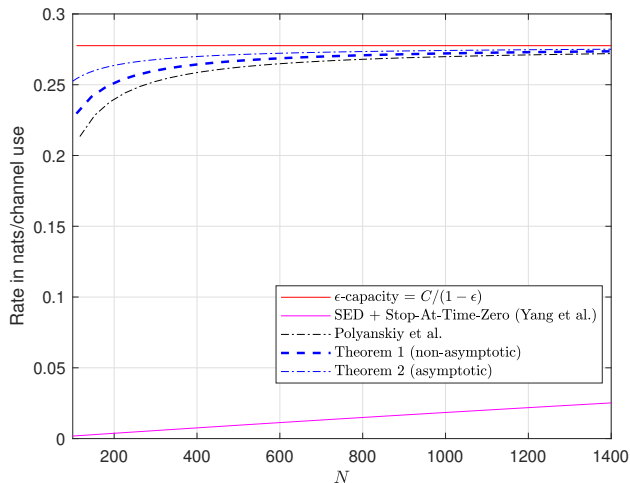
- Polyanskiy et al.'s bound outperforms SED code for this channel.

Channel: Cascade of BSC(0.11) and BEC(0.2)



- Our non-asymptotic bound outperforms Polyanskiy et al.'s and SED.

Channel: Cascade of BSC(0.11) and BEC(0.2)



- Our asymptotic bound is shown.

- We desire universality in code design because the channel statistics are not always available.
- The goal is to develop coding schemes whose performance is not so below from that of codes specific to a particular channel.
- An (N, M, ϵ) -UVLF code is such that

f_n and g cannot depend on $P_{Y|X}$

- $M_U^*(N, \epsilon) = \{\max M : \exists (N, M, \epsilon)\text{-UVLF code}\}$

- We universalize our previous code by employing a universal decoding metric.
- Empirical distribution:

$$\hat{P}_{x^n}(a) = \sum_{i=1}^n \frac{1}{n} 1\{x_i = a\}$$

- Instead of information density $i(X^n; Y^n)$, the decoder uses the **empirical mutual information** $nI(\hat{P}_{\mathbf{c}^n(m)}, \hat{P}_{Y^n|\mathbf{c}^n(m)})$
- Only a **single communication phase** is employed:

$$\tau^{(1)} = \inf\{n \geq 1: \max_{m \in [M]} nI(\hat{P}_{\mathbf{c}^n(m)}, \hat{P}_{Y^n|\mathbf{c}^n(m)}) > \gamma_1\}$$

- This decoder keeps track of the empirical MI of each codeword and decodes as soon as one of them is larger than γ_1 .
- We employ the stop-at-time-zero strategy similar to the known-channel case.

Theorem 3

Assume that a capacity-achieving distribution for the channel is known. Assume that $C > 0$ and $C_1 < \infty$. Then,

$$\log M_{\text{U}}^*(N, \epsilon) \geq \frac{NC}{1 - \epsilon} - \log N - \min \left\{ \frac{|\mathcal{X}||\mathcal{Y}|}{2}, \left(|\mathcal{X}| - \frac{3}{2} \right) \left(|\mathcal{Y}| - \frac{3}{2} \right) + \frac{3}{4} \right\} \log N + O(\log \log N).$$

If $P_{Y|X}$ is known to be a BSC with an unknown flip probability $p \in (0, 1) \setminus \{\frac{1}{2}\}$,

$$\log M_{\text{U}}^*(N, \epsilon) \geq \frac{NC}{1 - \epsilon} - \frac{3}{2} \log N + o(\log \log N).$$

- When $P_{Y|X}$ is known, $-\log N$ is achieved by Polyanskiy et al.'s single-phase scheme.
- We characterize a **penalty term** of order $\log N$ due to not knowing the channel.

Lemma 1 (Woodroffe Th. 4.5)

Let $g: \mathbb{R}^k \rightarrow \mathbb{R}$ be a twice differentiable continuous function. Let $Y_1, Y_2, \dots \in \mathbb{R}^k$ be i.i.d. random vectors. Let $\mu = g(\mathbb{E}[Y_1]) > 0$. Let $\gamma > 0$. Define

$$Z_n = ng \left(\frac{1}{n} \sum_{i=1}^n Y_i \right), \quad \tau = \inf\{n \geq 1: Z_n > \gamma\}.$$

As $\gamma \rightarrow \infty$

$$\mathbb{E}[\tau] = \frac{1}{\mu} \left(\gamma + \underbrace{\rho - \frac{1}{2} \text{tr}(\text{Cov}(Y_1) \nabla^2 g(\mathbb{E}[Y_1]))}_{O(1)} \right) + o(1)$$

where $\rho = \frac{\mathbb{E}[S_{\tau+}^2]}{2\mathbb{E}[S_{\tau+}]}$ with $S_n = n\mu + \sum_{i=1}^n \nabla g(\mathbb{E}[Y_1])^\top (Y_i - \mathbb{E}[Y_1])$, and $\tau^+ = \inf\{n \geq 1: Z_n > 0\}$.

Lemma 1 (Woodroffe Th. 4.5)

Let $g: \mathbb{R}^k \rightarrow \mathbb{R}$ be a twice differentiable continuous function. Let $Y_1, Y_2, \dots \in \mathbb{R}^k$ be i.i.d. random vectors. Let $\mu = g(\mathbb{E}[Y_1]) > 0$. Let $\gamma > 0$. Define

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As $\gamma \rightarrow \infty$

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- **Application:** We choose g to be the mutual information function. $Z_n = nI(\hat{P}_{X^n}, \hat{P}_{Y^n|X^n})$ and $S_n = \iota(X^n; Y^n)$ evaluated at P_{XY} . We get $\mathbb{E}[\tau] = \frac{\gamma}{C} + O(1)$ as in the known-channel case.

Lemma 2

Let $(\bar{X}^n, Y^n) \sim P_{\bar{X}}^n P_Y^n$ and let $\gamma > 0$. Assume that $P_X(x) > 0$ and $P_Y(y) > 0$ for all (x, y) . Then,

$$\mathbb{P} \left[nI(\hat{P}_{\bar{X}^n}, P_{Y^n|\bar{X}^n}) \geq \gamma \right] \leq K_1(n+1)^d \exp\{-\gamma\}$$
$$d = \min \left\{ \frac{|\mathcal{X}||\mathcal{Y}| - 2}{2}, \left(|\mathcal{X}| - \frac{3}{2} \right) \left(|\mathcal{Y}| - \frac{3}{2} \right) - \frac{1}{4} \right\}$$

where K_1 is a positive constant depending only on $|\mathcal{X}|$ and $|\mathcal{Y}|$. By the union bound,

$$\mathbb{P} \left[\exists n \leq n_0 : nI(\hat{P}_{\bar{X}^n}, P_{Y^n|\bar{X}^n}) \geq \gamma \right] \leq K_1(n_0 + 1)^{d+1} \exp\{-\gamma\}$$

- For comparison: $\mathbb{P} \left[\exists n \in \mathbb{N} : \iota(\bar{X}^n; Y^n) \geq \gamma \right] \leq \exp\{-\gamma\}$
- Method of types: $\mathbb{P} \left[nI(\hat{P}_{\bar{X}^n}, P_{Y^n|\bar{X}^n}) \geq \gamma \right] \leq (n+1)^{|\mathcal{X}||\mathcal{Y}|-1} \exp\{-\gamma\}$

- We develop a novel VLF code and analyze its performance, which improves the best achievability bound known.
- We universalize our code by employing empirical mutual information and characterize the back-off from the known-channel scenario.
- We extend our results to the Gaussian channel, where the universal metric becomes the mutual information assuming that the input-output pair is jointly Gaussian.

Thank you!