

Non-Asymptotic Analysis of Single-Receiver Channels with Limited Feedback

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1 Motivation

2 Dissertation

- Moderate Deviations Analysis of Point-to-Point Channels
- Variable-Length Sparse Stop-Feedback Codes
- Random Access Channels with Sparse Stop-Feedback

3 Conclusion and Future Directions

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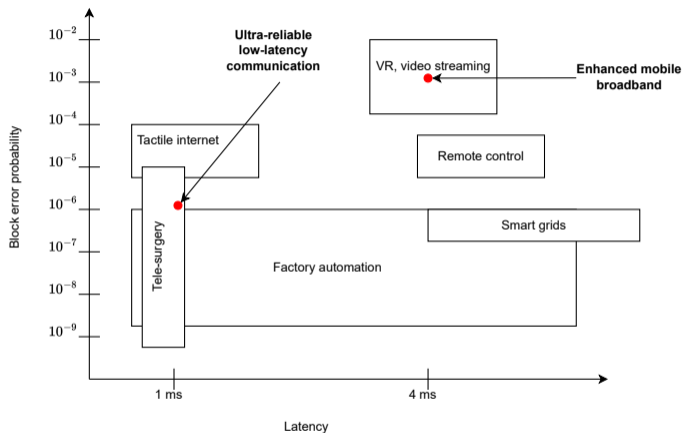
3 Conclusion and Future Directions

5G and newer generation networks offer three new service categories

- Ultra-reliable low-latency communication
 - ▶ Delay-sensitive, mission critical applications (tele-surgery, factory automation)
- Enhanced mobile broadband
 - ▶ High bandwidth and low power consumption requirements (HD video streaming, virtual reality)
- Massive machine-type communication
 - ▶ Massive and unknown number of communicating devices with low power consumption (Internet of Things, smart cities, smart grids)

Goal: Design coding schemes that are suitable for applications like these, analyze their performance, and understand the fundamental limits from an information-theoretic perspective.

Applications with Stringent Requirements



1 ms latency $\approx n = 100-200$

M. Shirvanimoghaddam et al., "Short Block-Length Codes for Ultra-Reliable Low Latency Communications", IEEE Commun. Mag., Feb. 2019.

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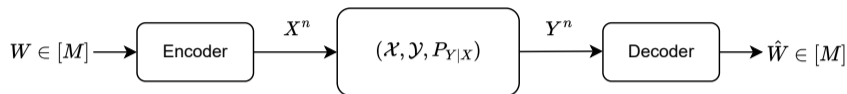
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- M = codebook size, n = blocklength, ϵ = average error probability, $[M] \triangleq \{1, \dots, M\}$.
- **Fundamental limit:** $M^*(n, \epsilon)$ = maximum achievable codebook size compatible with n and ϵ
- **Goal:** Compute $M^*(n, \epsilon)$ and find the optimal codes that achieve it
- **Problem:** Exact computation of $M^*(n, \epsilon)$ is intractable
- **Solution:** Derive non-asymptotic bounds

$$\underline{M}^*(n, \epsilon) \leq M^*(n, \epsilon) \leq \overline{M}^*(n, \epsilon)$$

- Example of non-asymptotic bound [Polyanskiy 10', random coding union bound]:

$$\underline{M}^*(n, \epsilon) = \max\{M : \mathbb{E} [\min\{1, (M-1)\mathbb{P}[\iota(\bar{X}^n; Y^n) \geq \iota(X^n; Y^n) | X^n, Y^n]\}] \leq \epsilon\}$$

The “solution” is an optimization problem

- ▶ it does not make clear how $M^*(n, \epsilon)$ varies with $(P_{Y|X}, n, \epsilon)$
 - ▶ even approximately computing it is nontrivial
- We are interested in **asymptotic expansions** (Taylor-like expansions of $\frac{\log M^*(n, \epsilon)}{n}$ around capacity) that
 - ▶ are tight for $(P_{Y|X}, n, \epsilon)$ of interest
 - ▶ inform about how $M^*(n, \epsilon)$ varies with $(P_{Y|X}, n, \epsilon)$
 - ▶ cover a variety of channels
 - Analyzing $M^*(n, \epsilon)$ as $n \rightarrow \infty$ is useful!

As $n \rightarrow \infty$, we need to specify how ϵ is related to n

- **Central limit theorem (CLT) regime:**

$$\epsilon \in (0, 1)$$

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

$$C = \text{capacity}$$

- **Moderate deviations (MD) regime**

$$\epsilon \rightarrow 0 \text{ and } -\frac{1}{n} \log \epsilon \rightarrow 0 \qquad \log M^*(n, \epsilon) = nC - g(n), \quad \sqrt{n} \ll g(n) \ll n$$

- **Large deviations (LD) regime:**

$$\epsilon \approx e^{-nE(R)}$$

$$\log M^*(n, \epsilon) = nR, \quad R < C$$

MD regime is relevant to ultra-reliable short-blocklength regime where both ϵ and n are small.

CLT and LD regimes fail to capture this regime.

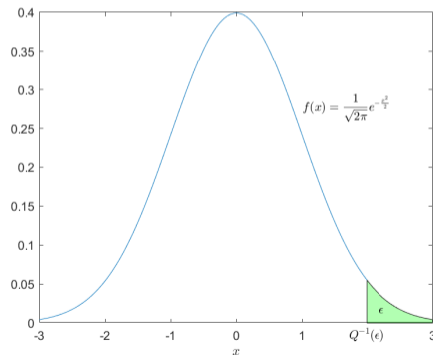
- [Strassen 62'] and [Polyanskiy et al. 10'] show

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

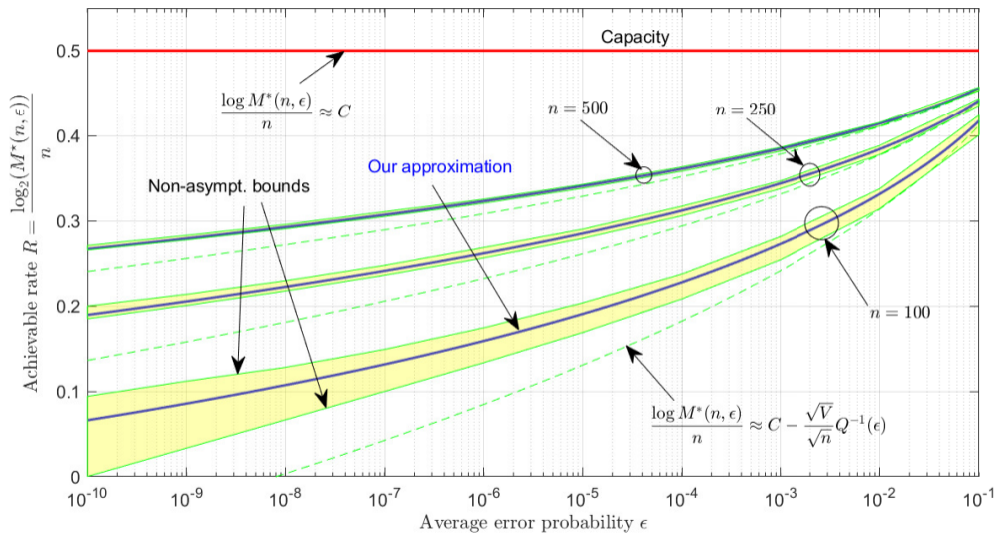
C = capacity

V = dispersion (a quantity that depends only on $P_{Y|X}$)

$Q^{-1}(\cdot)$ = inverse of $Q(\cdot)$, complementary cumulative distribution function of $\mathcal{N}(0, 1)$



How do asymptotic expansions for $\log M^*$ perform?



Non-Gaussianity:

$$\zeta(n, \epsilon) \triangleq \log M^*(n, \epsilon) - \underbrace{\left(nC - \sqrt{nV}Q^{-1}(\epsilon) \right)}_{\text{Gaussian approximation}}$$

- ① **CLT**: [Polyanskiy et al. 10'] (achievability) and [Tomamichel-Tan 13'] (converse): for nonsingular channels

excludes a family of erasure channels

$$\zeta(n, \epsilon) = \frac{1}{2} \log n + O(1)$$

- ② **CLT**: [Moulin 17']: for nonsingular channels with a regularity condition (excludes the BSC)

$$\zeta(n, \epsilon) \geq \frac{1}{2} \log n + \underline{S}Q^{-1}(\epsilon)^2 + \underline{B} + o(1)$$

$$\zeta(n, \epsilon) \leq \frac{1}{2} \log n + \overline{S}Q^{-1}(\epsilon)^2 + \overline{B} + o(1)$$

where $\underline{S}, \overline{S}, \underline{B}$, and \overline{B} depend only on $P_{Y|X}$

- **MD:** [Altuğ and Wagner 14']:

$$\zeta(n, \epsilon_n) = o(\sqrt{n}Q^{-1}(\epsilon_n))$$

Gaussian approximation (without $O(\log n)$ term) is valid in the MD regime

- **Question:** How does the non-Gaussianity $\zeta(n, \epsilon_n)$ scale in the MD regime?

- **A new operational quantity:** Channel skewness

$$S \triangleq \lim_{\epsilon \rightarrow 0} \liminf_{n \rightarrow \infty} \frac{\zeta(n, \epsilon) - \frac{1}{2} \log n}{(Q^{-1}(\epsilon))^2}$$

We are expecting:

$$\log M^*(n, \epsilon_n) = nC - \sqrt{nV}Q^{-1}(\epsilon_n) + \frac{1}{2} \log n + SQ^{-1}(\epsilon_n)^2 + o(Q^{-1}(\epsilon_n)^2)$$

- Information density: $\iota(X; Y) \triangleq \log \frac{P_{Y|X}(Y|X)}{P_Y(Y)}$ under some fixed input distribution P_X

$$\left. \begin{aligned} C &= \mathbb{E}[\iota(X; Y)] \\ V &= \text{Var}[\iota(X; Y)] \end{aligned} \right\} \text{ under capacity-achieving } P_X$$

S = governed by the third central moment of information density

ϵ_n in MD regime: $-\frac{1}{n} \log \epsilon_n \rightarrow 0$, $\epsilon_n \rightarrow 0$

Theorem 1

MD: for nonsingular discrete memoryless point-to-point channels

$$\zeta(n, \epsilon_n) \geq \frac{1}{2} \log n + \underline{S} Q^{-1}(\epsilon_n)^2 + O\left(\frac{Q^{-1}(\epsilon_n)^3}{\sqrt{n}}\right) + O(1)$$

$$\zeta(n, \epsilon_n) \leq \frac{1}{2} \log n + \overline{S} Q^{-1}(\epsilon_n)^2 + O\left(\frac{Q^{-1}(\epsilon_n)^3}{\sqrt{n}}\right) + O(1)$$

- \underline{S} and \overline{S} are the same as Moulin's bounds, and our results apply to a wider class of channels
- \underline{S} and \overline{S} are **easy-to-compute** constants that depend only on the channel $P_{Y|X}$ and are related to $\iota(X; Y)$
- \underline{S} and \overline{S} give lower and upper bounds for channel skewness S
- $\frac{1}{2} \log n + O(1)$ is no longer accurate because as $n \rightarrow \infty$, $\epsilon_n \rightarrow 0$ and $Q^{-1}(\epsilon_n)^2 \rightarrow \infty$

- Lower bound is achieved using i.i.d. random codewords drawn from a distribution P_X that is shifted from the capacity-achieving P_X^*

$$P_X = P_X^* + \frac{Q^{-1}(\epsilon_n)}{\sqrt{n}} \mathbf{h}$$

\mathbf{h} = a vector that is a function of $P_{Y|X}$

- For Cover-Thomas symmetric channels (all rows (resp. columns) are permutation of each other), e.g., BSC

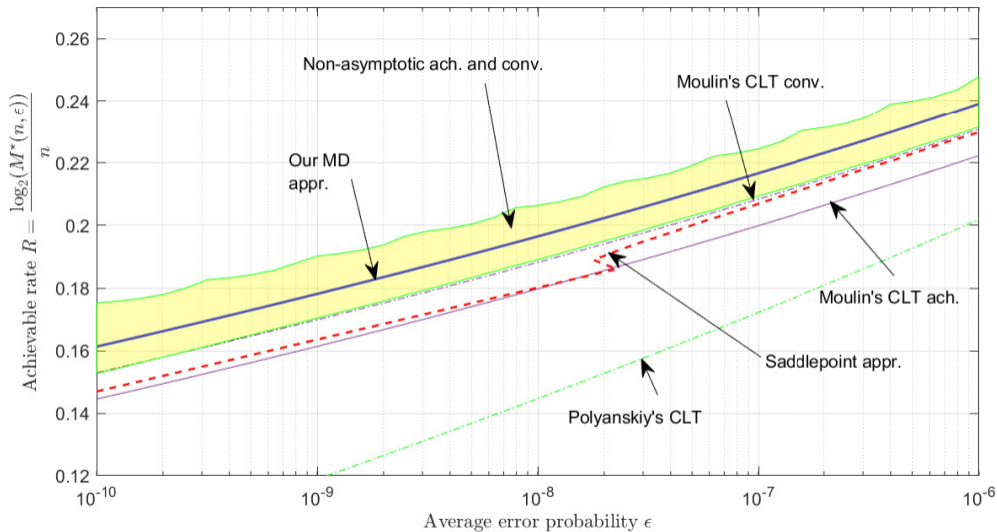
$$S = \bar{S} = \underline{S} = \frac{\text{Sk}(P_X^*)\sqrt{V}}{6} + \frac{1}{2}$$

$$P_X = P_X^*$$

$$\text{Sk}(P_X^*) = \text{skewness of } \iota(X; Y) \text{ at } P_X^*$$

- For the Gaussian channel, we compute the channel skewness $S(P)$ exactly as a function of power P

Comparison of Our Approximation to Existing Work



Achievable rates for BSC(0.11), $n = 200$.

- We relax the random coding union bound from [Polyanskiy et al. 10'] as

$$\begin{aligned} P_{\text{error}} &\leq \mathbb{E} \left[\min\{1, (M-1)\mathbb{P}[\iota(\bar{X}^n; Y^n) \geq \iota(X^n; Y^n) | X^n, Y^n]\} \right] \\ &\leq \mathbb{P}[\iota(X^n; Y^n) < \tau] + (M-1)\mathbb{P}[\iota(\bar{X}^n; Y^n) \geq \iota(X^n; Y^n) \geq \tau] \end{aligned}$$

where \bar{X}^n is a sample from the codebook that is independent of Y^n .

- ▶ Relaxation of the ML decoder (information density threshold rule + ML rule)
- ▶ Advantageous because we can analyze each probability term separately

- The optimal allocation of ϵ_n (equivalently, the optimal τ) is:

$$\underbrace{\mathbb{P}[\iota(X^n; Y^n) < \tau]}_{\epsilon_n - \epsilon_n \frac{Q^{-1}(\epsilon_n)}{\sqrt{nV(P_X)}}} + (M-1) \underbrace{\mathbb{P}[\iota(\bar{X}^n; Y^n) \geq \iota(X^n; Y^n) \geq \tau]}_{\epsilon_n \frac{Q^{-1}(\epsilon_n)}{\sqrt{nV(P_X)}}$$

- $\mathbb{P}[\iota(X^n; Y^n) < \tau]$: MD regime of probability theory
- $\mathbb{P}[\iota(\bar{X}^n; Y^n) \geq \iota(X^n; Y^n) \geq \tau]$: LD regime of probability theory

Theorem 2 (Petrov Expansion)

Let X_1, \dots, X_n be i.i.d., $\mathbb{E}[X_1] = 0$ and $\text{Var}[X] = \sigma^2$. Let $x = o(\sqrt{n})$, and $x \geq 0$. Under Cramér's condition, i.e., $\mathbb{E}[e^{tX}] < \infty$ in the neighborhood of zero,

$$\mathbb{P} \left[\sum_{i=1}^n X_i \geq \sqrt{n\sigma^2}x \right] = Q(x) \exp \left(\frac{x^3 \text{Sk}(X_1)}{6\sqrt{n}} + O \left(\frac{x^4}{n} \right) \right) \left(1 + O \left(\frac{1+x}{\sqrt{n}} \right) \right)$$

where $\text{Sk}(X_1) \triangleq \frac{\mathbb{E}[X_1^3]}{\sigma^3}$.

- It is an asymptotic equality
- It has a multiplicative correction term to Gaussian approximation $Q(x)$
- Skewness $\text{Sk}(X_1)$ dominates the correction term

- $\mathbb{P}[\iota(X^n; Y^n) < \tau]$: Apply Petrov expansion
- $\mathbb{P}[\iota(\bar{X}^n; Y^n) \geq \iota(X^n; Y^n) \geq \tau]$: Apply strong large deviations theorem to get

$$\begin{aligned} \log M^* &\geq nI(P_X) - \sqrt{nV(P_X)}Q^{-1}(\epsilon_n) + \frac{1}{2} \log n \\ &\quad + Q^{-1}(\epsilon_n)^2 \left(\frac{\text{Sk}(P_X)\sqrt{V(P_X)}}{6} + \frac{1 - \eta(P_X)}{2(1 + \eta(P_X))} \right) + O\left(\frac{Q^{-1}(\epsilon_n)^3}{\sqrt{n}}\right) + O(1) \end{aligned}$$

- Take Taylor series expansions around the capacity-achieving P_X^* .

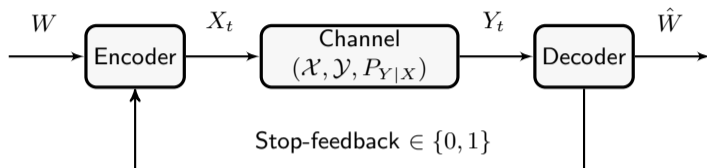
- ① In the MD regime of channel coding:
 - ▶ We derive easy-to-compute lower and upper bounds to the non-Gaussianity
 - ▶ For symmetric channels, the bounds match each other, and channel skewness S is governed by the skewness of information density $\iota(X; Y)$
 - ▶ Our MD approximation is more accurate than the CLT approximation of Polyanskiy, especially for lower error probabilities (e.g., $\epsilon \leq 10^{-6}$)
- ② For some non-symmetric channels, capacity-achieving distribution does not achieve S .
- ③ We compute the skewness of the Gaussian channel.

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- **Variable-Length Sparse Stop-Feedback Codes**
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3 Conclusion and Future Directions



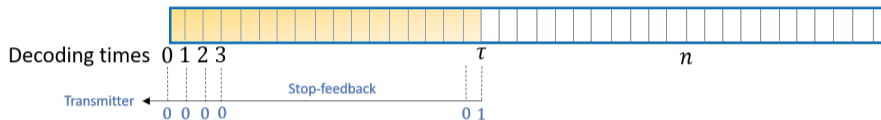
Variable-length: Decoding occurs at a random time depending on channel outputs

Stop-feedback: 1 bit feedback *whenever* a decoding attempt is made

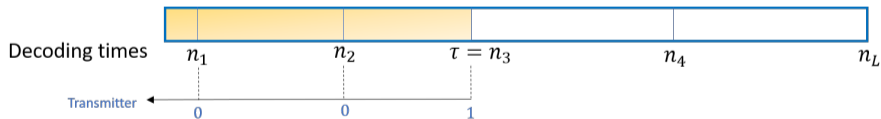
Higher reliability: Earlier decoding when the noise is low, later decoding when the noise is high

Why Sparse Stop-Feedback?

- VLSF code with $L = \infty$ decoding times [Polyanskiy et al. 11'], [Burnashev 76']: **Impractical**

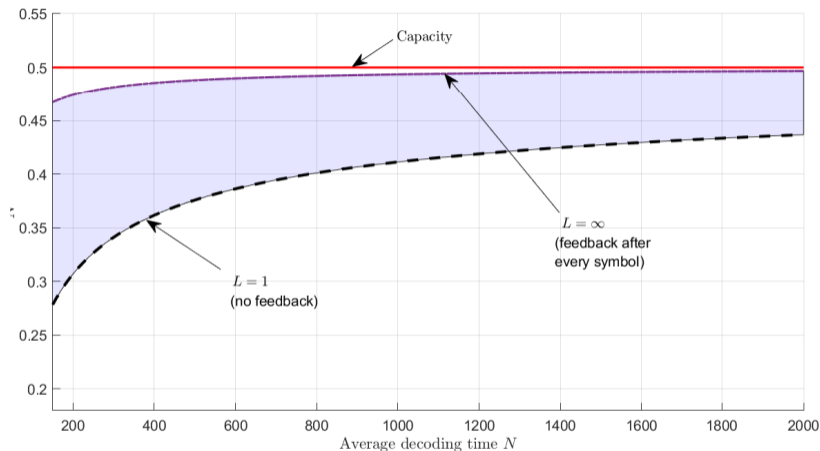


- ▶ Transmitter constantly listens to the feedback signal \implies High power consumption
 - ▶ Half duplex devices cannot transmit and receive signals at the same time \implies Lowers achievable rates due to round trip delay
 - ▶ Practical codes such as HARQ schemes employ incremental redundancy which has sporadic feedback
- VLSF code with constant L decoding times (this work)



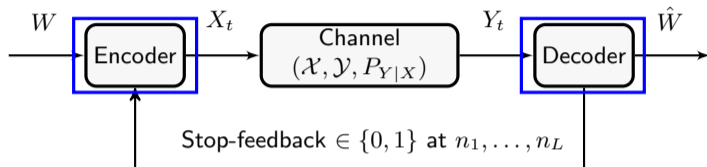
- ▶ Feedback is sporadic

No-Feedback Codes vs. VLSF Codes



$L = \#$ of available decoding times

What rate can we achieve with several decoding times?

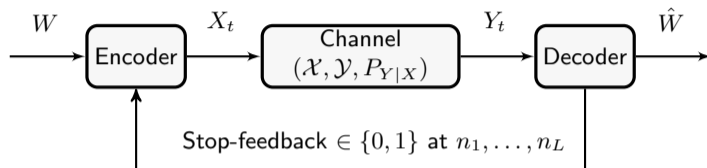


Encoding function $f_t: [M] \rightarrow \mathcal{X}$:

$$X_t = f_t(W), \quad t \in \mathbb{N}_+$$

where $W \sim \text{Unif}([M])$.

Decoding function $g_t: \mathcal{Y}^t \rightarrow [M]$: provides the estimate of W at time $t \in \{n_1, n_2, \dots, n_L\}$.



Stopping time: $\tau \in \{n_i\}_{i=1}^L$ adapted to the filtration generated by $\{Y^{n_i}\}_{i=1}^L$

Decoded message: $\hat{W} = g_\tau(Y^\tau)$

Goal: Find

$$M^*(N, L, \epsilon) \triangleq \max_{n_1, \dots, n_L} M$$

$$\text{s.t. } \mathbb{E}[\tau] \leq N$$

$$\mathbb{P}[\hat{W} \neq W] \leq \epsilon$$

$L = \infty$:

- [Burnashev 76']: error exponent $\lim_{\epsilon \rightarrow 0} \frac{-\log \epsilon}{\mathbb{E}[\tau]}$ for the discrete memoryless point-to-point channel as $N \rightarrow \infty$
- [Polyanskiy et al. 11']: VLSF codes in the CLT regime

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

$$\log M^*(N, 1, \epsilon) = NC - \sqrt{NV}Q^{-1}(\epsilon) + O(\log N)$$

Constant L :

- [Vakilinia et al. 16']: VLSF codes with L decoding times over the binary-input Gaussian channel
- They estimate the statistics of τ through simulation.
- They do not solve the problem analytically \implies **no second-order analysis**

Theorem 3 (Achievability)

Fix $L \geq 2$, $\epsilon \in (0, 1)$. For discrete memoryless point-to-point channels, it holds that

$$\log M^*(N, L, \epsilon) \geq \frac{NC}{1-\epsilon} - \sqrt{N \log_{(L-1)}(N) \frac{V}{1-\epsilon}} + o(\sqrt{N})$$

$$\log_{(L)}(\cdot) \triangleq \overbrace{\log(\log(\dots(\log(\cdot))))}^{L \text{ times}}$$

- Proof analyzes a non-asymptotic bound
- By using refined probability tools and KKT conditions, we approximately optimize the non-asymptotic bound with respect to the choices of n_1, \dots, n_L

Performance of VLSF Codes with L Decoding Times

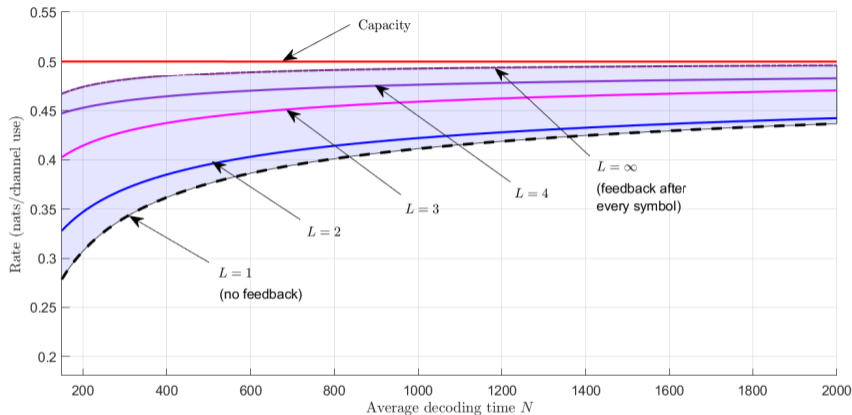


Figure 1: BSC(0.11), $\epsilon = 10^{-3}$

Diminishing performance improvement as L increases!

Sequential Hypothesis Tests (SHTs)

- Consider two hypotheses for the distribution of X^∞

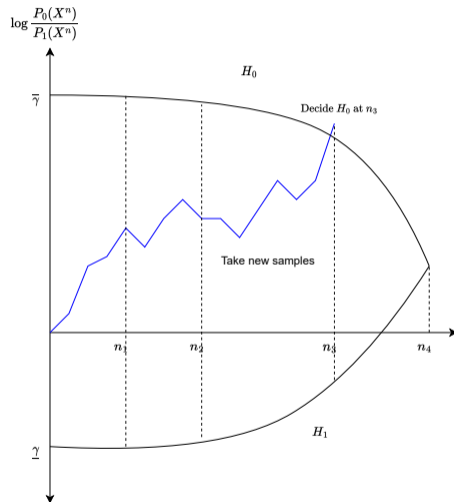
$$H_0: X^\infty \sim P_0^\infty$$

$$H_1: X^\infty \sim P_1^\infty$$

- At each available decoding time, an SHT chooses between

{Decide H_0 , Decide H_1 , Take new sample(s)}

- Wald's theorem: the optimal SHT is a two-sided threshold test that uses log-likelihood ratio (sequential version of Neyman-Pearson lemma)



- Construct the SHT

$H_0 : (X, Y) \sim P_X P_{Y|X} \implies$ stop and decode

$H_1 : (X, Y) \sim P_X P_Y \implies$ eliminate from decoding

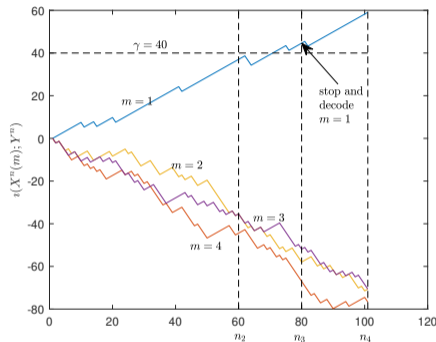
where P_X is capacity-achieving and run it for all M messages separately

- At time $n_1 = 0$:

- With probability $p = \epsilon - \frac{1}{\sqrt{N \log N}}$, declare H_1 for all $m \in [M]$
- With probability $1 - p$, pass $n_1 = 0$ without decoding

- If $n_1 = 0$ is passed, then particularize the SHT to information-density threshold test:

$$\tau_m = \min\{n \in \{n_2, \dots, n_L\} : \iota(X^n(m); Y^n) \geq \gamma\}$$



- Analyzing this scheme gives us a non-asymptotic bound. Then, we optimize over n_1, \dots, n_L using KKT conditions.

Maximal power constraint:

$$\|\mathbf{f}(m)^{n_\ell}\|_2^2 \leq n_\ell P \quad \forall \ell \in [L], m \in [M]$$

Theorem 4

Fix $L \geq 2$, $P > 0$, and $\epsilon \in (0, 1)$.

$$\log M_{\max}^*(N, L, \epsilon, P) \geq \frac{NC(P)}{1 - \epsilon} - \sqrt{N \log_{(L-1)}(N) \frac{V(P)}{1 - \epsilon}} + o(\sqrt{N})$$

where

$$C(P) = \frac{1}{2} \log(1 + P), \quad V(P) = \frac{P(P + 2)}{2(P + 1)^2}$$

- **Encoder:** we generate codewords uniformly at random over a restricted subset on n_L -dimensional sphere

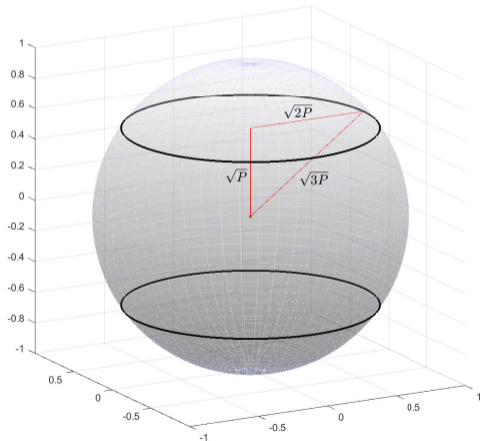
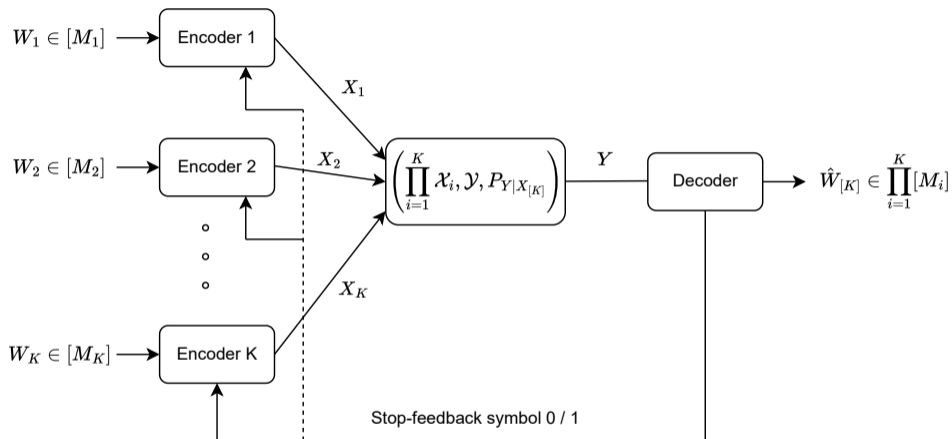


Figure 2: $L = 2$,
 $n_1 = 2, n_2 - n_1 = 1$

Discrete Memoryless Multiple Access Channel (MAC)



- $\{n_1, \dots, n_L\}$ = the set of available decoding times
- $\tau \in \{n_1, \dots, n_L\}$ = stopping time

- $X_{[K]} \triangleq X_1, \dots, X_K$

Goal: Find

$$\begin{aligned} \max_{n_1, \dots, n_L} \quad & \sum_{k=1}^K \log M_k \\ \text{s.t.} \quad & \mathbb{E}[\tau] \leq N \\ & \mathbb{P} \left[(\hat{W}_1, \dots, \hat{W}_K) \neq (W_1, \dots, W_K) \right] \leq \epsilon \end{aligned}$$

Theorem 5 (Achievability)

There exists a VLSF code with L decoding times for the discrete memoryless MAC satisfying

$$\sum_{k=1}^K \log M_k = \frac{N I_K}{1 - \epsilon} - \sqrt{N \log_{(L-1)}(N) \frac{V_K}{1 - \epsilon}} + o(\sqrt{N})$$

$$I_K = I(X_1, \dots, X_K; Y), \quad V_K = \text{Var}[\iota(X_1, \dots, X_K; Y)]$$

- Proof: We employ a single information density threshold decoder $\iota(X_{[K]}^{n_\ell}(m_{[K]}); Y^{n_\ell}) \geq \gamma$.

- Second-order achievability bounds for sparse VLSF codes over point-to-point and multiple access channels
- Optimizing the placements of L decoding times is critical to achieve high rates
- A handful of decoding times is almost as good as decoding after every symbol
For the BSC(0.11) at $N = 1000$ and $\epsilon = 10^{-3}$:

▶ $L = 4$ achieves 97.0% of the rate achieved by $L = \infty$

▶ $L = 1$ achieves 84.2% of the rate achieved by $L = \infty$

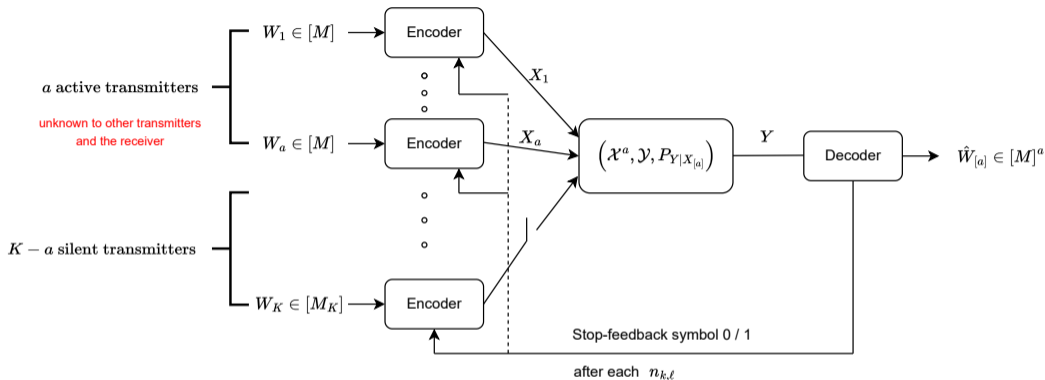
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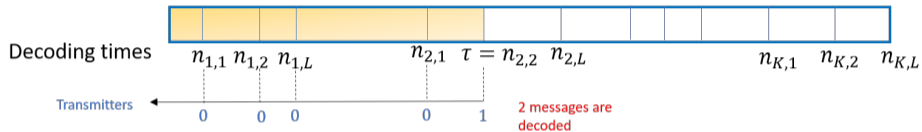
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Rateless RAC (Random Access Channel) Communication that Uses Stop-Feedback



- **RAC:** A family of MACs up to K transmitters, any $a \leq K$ transmitters can be active
- **Compound channel model:** No probability of being active is assigned to transmitters
- **Agnostic channel model:** Nobody knows who are active
- We extend VLSF codes to the RAC
- Available decoding times = $n_{a,1}, \dots, n_{a,L}$ for decoding $a \in [K]$ messages



Goal: Find

$$\begin{aligned} \max_{n_{a,\ell} : a \in [K], \ell \in [L]} \quad & M \\ \text{s.t.} \quad & \mathbb{E}[\tau_a] \leq N_a \quad a \in [K] \\ & \mathbb{P}[(\hat{W}_1, \dots, \hat{W}_a) \neq (W_1, \dots, W_a)] \leq \epsilon_a \quad a \in [K] \end{aligned}$$

- Presented in the candidacy talk.

Theorem 6 (Achievability)

Fix an input distribution P_X . For a RAC satisfying some mild symmetry conditions, there exists a RAC code with K transmitters provided that

$$a \log M \leq N_a I_a - \sqrt{N_a V_a} Q^{-1}(\epsilon_a) - \frac{1}{2} \log N_a + O(1) \quad \forall a \in [K]$$

We achieve the same first- and second-order terms as the best-known codes (e.g., [Tan-Kosut 14'], [Scarlett et al. 15]) for the MAC in operation.

- Proof: At times $n_{1,1}, \dots, n_{K,1}$, we use information density threshold rule

- Presented in the candidacy talk.

Theorem 7

There exists a RAC code for the Gaussian RAC with K transmitters provided that

$$a \log M \leq N_a C(aP) - \sqrt{N_a V_a(P)} Q^{-1}(\epsilon_a) + \frac{1}{2} \log N_a + O(1) \quad \forall a \in [K]$$

where

$$C(P) = \frac{1}{2} \log(1 + P), \quad V_a(P) = \frac{(2a^2 - a)P^2 + 2aP}{2(aP + 1)^2}$$

- Proof analyzes the error probability of the random code where codewords are generated uniformly on the restricted power sphere

Theorem 8 (Achievability)

Fix $K, L \geq 2$, $\epsilon \in (0, 1)$, and a distribution P_X . Under some mild symmetry conditions, there exists a VLSF code for the discrete memoryless RAC with L decoding times for each $a \in [K]$ provided that

$$a \log M \leq \frac{N_a I_a}{1 - \epsilon_a} - \sqrt{N_a \log_{(L-1)}(N_a) \frac{V_a}{1 - \epsilon_a}} + o(\sqrt{N_a}) \quad \forall a \in [K]$$

We achieve the same first- and second-order terms as the MAC in operation

- **Decoder:** At time n_0 , the decoder applies a multiple hypothesis test to estimate # of active transmitters a . If \hat{a} is decoder's estimate, decoder uses a VLSF code for the \hat{a} -MAC with decoding times $\{n_{\hat{a},1}, \dots, n_{\hat{a},L}\}$

1 Motivation

2 Dissertation

- Moderate Deviations Analysis of Point-to-Point Channels
- Variable-Length Sparse Stop-Feedback Codes
- Random Access Channels with Sparse Stop-Feedback

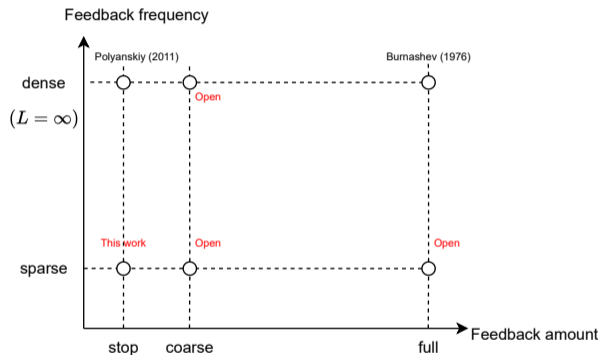
3 Conclusion and Future Directions

- In the low-latency, high-reliability regime, our MD approximation is more accurate than several state-of-the-art approximations
- In this regime, channel skewness cannot be neglected to get tight approximations

- A handful of decoding times in VLSF codes achieve rates close to those achieved by $L = \infty$

- For RACs, we achieve the same first- and second-order rates as if the active transmitters are known a priori
- Rateless coding with stop-feedback enables this result

- Different ways of limiting the feedback in VLSF codes:



- ▶ Coarse feedback: Send R_f bits of feedback at each time
- ▶ In many applications, we can send bursty feedback

- **A tight converse for VLSF codes with L decoding times** is missing
- Towards this goal, we have a non-asymptotic converse bound based on fundamental limits of SHTs
This bound seems to be very challenging to analyze

- **Second-order converse for the RAC result:**

- ▶ A second-order converse result for the K -MAC is also a converse result for the RAC
- ▶ However, it is a long-standing open problem
- ▶ [Kosut 22'] proves that the second-order term scales as $-O(\sqrt{N})$

$$K \log M^* = n_K I_K - O(\sqrt{n_K})$$

Thank you!

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