One-Shot Coding over General Noisy **Networks ISIT 2024**

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Background

Background



Some key questions of network information theory

- Blocklength in information transmission: asymptoticity & finite blocklength & one-shot achievability?
- Noisy network coding: capacity of noisy networks & coding schemes?
- Onified Coding Scheme: channel coding & source coding?

Our contributions

- Part I: A unified one-shot coding framework for communication and compression of messages among multiple nodes across a general acyclic noisy network.
 - Proof technique: exponential process refinement lemma
- 2 Part II:
 - Novel one-shot achievability results discovered.
 - Existing one-shot & asymptotic results recovered.

Background: One-shot Information Theory



One-shot information theory

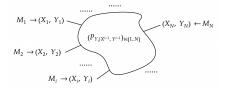
- Conventional Shannon theory: asymptotically optimal information transmission rates based on the law of large numbers (e.g., typicality).
- Finite-blocklength regime^a: maximal information transmission rate at a given blocklength and error probability?
- One-shot achievability^b: What if the blocklength can be as short as 1 (each source and channel is only used once)?
 - Sources and channels can be arbitrary: no need to be memoryless or ergodic.
 - 2 Can recover existing (first-order and second-order) asymptotic results when applied to memoryless sources and channels.

^aPolyanskiy, Yury, H. Vincent Poor, and Sergio Verdú. "Channel coding rate in the finite blocklength regime." IEEE Transactions on Information Theory 56, no. 5 (2010): 2307-2359.

^bLi, Cheuk Ting, and Venkat Anantharam. "A unified framework for one-shot achievability via the Poisson matching lemma."IEEE Transactions on Information Theory 67, no. 5 (2021): 2624-2651.

Background: Noisy Network Coding





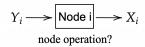
Noisy Network Coding

- Noisy network coding^a: communicating messages between multiple sources and destinations over a general noisy network.
- Generalizing:
 - Noiseless network coding by Ahlswede, Cai, Li and Yeung.
 - 2 Compress-forward coding for relay channels by Cover and El Gamal.
 - Odding for relay networks, coding for erasure networks, etc.

^aLim, Sung Hoon, Young-Han Kim, Abbas El Gamal, and Sae-Young Chung. "Noisy network coding." IEEE Transactions on Information Theory 57, no. 5 (2011): 3132-3152.

Background: A Unified Random Coding Bound





Unified random coding bound

- Unified random coding bound via blockwose node operation^a: work for any combination of channel coding and source coding
- 2 Advantages:
 - Unifying and generalizing known relaying strategies, can yield good bounds without error analysis.
 - Useful for designing automated theorem proving tools^b.

^aLee, Si-Hyeon, and Sae-Young Chung. "A unified random coding bound."IEEE Transactions on Information Theory 64, no. 10 (2018): 6779-6802.

^bLi, Cheuk Ting. "An automated theorem proving framework for information-theoretic results."IEEE Transactions on Information Theory (2023).

Our contributions

Background

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- 1 A unified one-shot coding scheme
- over general noisy acyclic discrete networks (ADN)
- that is applicable to any combination of source coding, channel coding and coding for computing problems.

Special cases

- Novel one-shot achievablity results for:
 - One-shot relay channels
 - One-shot primitive relay channels
 - Compress-and-forward bound
 - Partial-decode-and-forward bound
 - Recovered one-shot & asymptotic results on:
 - Source and channel coding
 - @ Gelfand-Pinsker, Wyner-Ziv and coding for computing
 - Multiple access channels
 - Broadcast channels

Background

Poisson functional representation

- For a finite set \mathcal{U} , let $\mathbf{U} := (Z_u)_{u \in \mathcal{U}}$ be i.i.d. $\operatorname{Exp}(1)$ random variables.
- Given a distribution P over \mathcal{U} , Poisson functional representation^a:

$$\mathbf{U}_P := \operatorname{argmin}_u \frac{Z_u}{P(u)}$$

- We have $U_P \sim P$.
- It can be viewed as a variant of the A* sampling, and have a wide range of applications: minimax learning, neural network compression and differential privacy.

^aLi, Cheuk Ting, and Abbas El Gamal. "Strong functional representation lemma and applications to coding theorems."IEEE Transactions on Information Theory 64, no. 11 (2018): 6967-6978.

Techniques



Poisson functional representation

Coding Scheme

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Given a distribution P over \mathcal{U} , Poisson functional representation:

$$\mathbf{U}_P := \operatorname{argmin}_u \frac{Z_u}{P(u)}$$

Generalized Poisson matching lemma

- Let $\mathbf{U}_{P}(1), \dots, \mathbf{U}_{P}(|\mathcal{U}|) \in \mathcal{U}$ be the elements of \mathcal{U} sorted in ascending order of $Z_u/P(u)$, let $\mathbf{U}_P^{-1}: \mathcal{U} \to [|\mathcal{U}|]$ for the inverse function of $i \mapsto \mathbf{U}_P(i)$.
- **Generalized Poisson matching lemma**^a: For distributions P, Q over \mathcal{U} , we have the following almost surely:

$$\mathsf{E}\left[\mathsf{U}_Q^{-1}(\mathsf{U}_P)\,\Big|\,\mathsf{U}_P\right] \leq \frac{P(\mathsf{U}_P)}{Q(\mathsf{U}_P)} + 1.$$

^aLi, Cheuk Ting, and Venkat Anantharam. "A unified framework for one-shot achievability via the Poisson matching lemma." IEEE Transactions on Information Theory 67. no. 5 (2021): 2624-2651.



Refining a distribution by an exponential process

Coding Scheme

For a joint distribution Q_{V,U} over V × U, the refinement of Q_{V,U} by U, denoted as Q^U_{V,U}, is a joint distribution

$$Q_{V,U}^{\mathbf{U}}(v,u) := \frac{Q_V(v)}{\left(\mathbf{U}_{Q_{U|V}(\cdot|v)}^{-1}(u)\sum_{i=1}^{|\mathcal{U}|}i^{-1}\right)}$$

for all (v, u) in the support of $Q_{V,U}$, where Q_V is the V-marginal of $Q_{V,U}$ and $Q_{U|V}$ is the conditional distribution of U given V.

- The refinement $Q_U^{\mathbf{U}}(u)$ is for the **soft decoding** of U, which gives a distribution over U, with \mathbf{U}_{Q_U} having the largest probability.
- Useful in non-unique decoding.
- If the distribution $Q_{V,U}$ represents our "prior distribution" of (V,U), then the refinement $Q_{V,U}^{\mathbf{U}}$ is our updated "posterior distribution" after taking the exponential process \mathbf{U} into account.

Exponential Process Refinement Lemma

Coding Scheme

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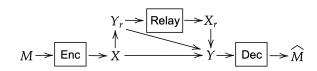
- To keep track of the evolution of the "posterior probability" of the correct values of a large number of random variables through the refinement process:
- For a distribution P over \mathcal{U} and a joint distribution $Q_{V,U}$ over a finite $\mathcal{V} \times \mathcal{U}$, for every $v \in \mathcal{V}$, we have, almost surely,

$$\mathbf{E}\left[\frac{1}{Q_{V,U}^{\mathbf{U}}(v,\mathbf{U}_{P})}\middle|\mathbf{U}_{P}\right] \leq \frac{\ln|\mathcal{U}|+1}{Q_{V}(v)}\left(\frac{P(\mathbf{U}_{P})}{Q_{U|V}(\mathbf{U}_{P}|v)}+1\right).$$

We use the following example to demonstrate how to use it.

One-Shot Relay Channel



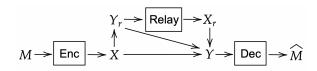


One-Shot Relay Channel

- **1** Encoder observes $M \sim \text{Unif}[L]$ and outputs X, which is passed through the channel $P_{Y_r|X}$.
- Relay observes Y_r and outputs X_r .
- 3 (X, X_r, Y_r) is passed through the channel $P_{Y|X,X_r,Y_r}$.
 - Y depends on all of X, X_r, Y_r and X_r may interfere with (X, Y_r) :
 - Possible when the relay outputs X_r instantaneously or the channel has a long memory, or it is a storage device.
- Decoder observes Y and recovers \hat{M} .

One-Shot Relay Channel



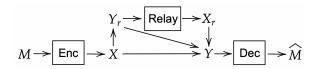


One-Shot Relay Channel

- Inherent limitation of one-shot setting: unable to model cyclic networks, e.g., two-way communication channels, general relay channels that depend on its past.
- Above: One-shot version of relay-with-unlimited-look-ahead ^a
- "Best one-shot approximation" of the conventional relay channel.

^aEl Gamal, Abbas, Navid Hassanpour, and James Mammen. "Relay networks with delays."IEEE Transactions on Information Theory 53, no. 10 (2007): 3413-3431.





Corollary

For any P_X , $P_{U|Y_r}$, function $x_r(y_r, u)$, there is a deterministic coding scheme for the one-shot relay channel such that the error probability satisfies

$$P_e \leq \textbf{E} \Big[\min \big\{ \gamma L 2^{-\iota(X;U,Y)} \big(2^{-\iota(U;Y) + \iota(U;Y_r)} + 1 \big), 1 \big\} \Big],$$

where $(X, Y_r, U, X_r, Y) \sim P_X P_{Y_r|X} P_{U|Y_r} \delta_{x_r(Y_r, U)} P_{Y|X, Y_r, X_r}$, and $\gamma := \text{In } |\mathcal{U}| + 1$.



Proof

Background

- **1** Auxiliaries: $U_1 := (X, M), U_2 := U$.
- 2 "Random codebooks" U_1 , U_2 : independent exponential processes.
- **3** Encoder: $U_1 = (\mathbf{U}_1)_{P_{U_1} \times \delta_M}$ (PFR), then outputs *X*-component of U_1 .
- **4** Relay: $U_2 = (\mathbf{U}_2)_{P_{U_2 \mid Y_r}(\cdot \mid Y_r)}$, then outputs $X_r = x_r(Y_r, U_2)$.
- Decoder observes Y. and:
 - Refine $P_{U_2|Y}(\cdot|Y)$ to $Q_{U_2}:=P_{U_2|Y}^{\mathbf{U}_2}$. By Exponential Process Refinement Lemma:

$$\boldsymbol{E}\bigg[\frac{1}{Q_{U_2}(U_2)}\bigg|\,U_2,Y,Y_\mathrm{r}\bigg] \leq (\ln|\mathcal{U}_2|+1)\left(\frac{P_{U_2|Y_\mathrm{r}}(U_2)}{P_{U_2|Y}(U_2)}+1\right).$$

- Let $\tilde{U}_1 = (\mathbf{U}_1)_{\tilde{Q}_{U_1} \times P_M}$, and output its *M*-component.

One-Shot Relay Channel



Proof

$$\begin{split} & \textbf{P}(\tilde{U}_{1} \neq U_{1} \mid X, Y_{\mathrm{r}}, U_{2}, X_{\mathrm{r}}, Y, M) \\ & \leq \textbf{E} \left[\min \left\{ \frac{P_{U_{1}}(U_{1})\delta_{M}(M)}{P_{U_{1}\mid U_{2}, Y}(U_{1}\mid U_{2}, Y)Q_{U_{2}}(U_{2})P_{M}(M)}, 1 \right\} \mid X, Y_{\mathrm{r}}, U_{2}, X_{\mathrm{r}}, Y, M \right] \\ & \stackrel{(b)}{=} \textbf{E} \left[\min \left\{ L \frac{P_{U_{1}}(U_{1})}{P_{U_{1}\mid U_{2}, Y}(U_{1}\mid U_{2}, Y)Q_{U_{2}}(U_{2})}, 1 \right\} \mid X, Y_{\mathrm{r}}, U_{2}, X_{\mathrm{r}}, Y, M \right] \\ & \stackrel{(c)}{\leq} \min \left\{ L \frac{P_{U_{1}}(U_{1})}{P_{U_{1}\mid U_{2}, Y}(U_{1}\mid U_{2}, Y)} (\ln |\mathcal{U}_{2}| + 1) \left(\frac{P_{U_{2}\mid Y_{\mathrm{r}}}(U_{2})}{P_{U_{2}\mid Y}(U_{2})} + 1 \right), 1 \right\} \\ & = \min \left\{ (\ln |\mathcal{U}_{2}| + 1) L2^{-\iota(X;U_{2}, Y)} \left(2^{-\iota(U_{2}; Y) + \iota(U_{2}; Y_{\mathrm{r}})} + 1 \right), 1 \right\}. \end{split}$$

(a) is by the Poisson matching lemma; (b) is by $\delta_M(M) = 1$, $P_M(M) = 1/L$; (c) is by the refinement step (previous page) and Jensen's inequality.

For some $P_{U|Y_r}$ and function $x_r(y_r, u_2)$, it yields the asymptotic achievable rate:

$$R \le I(X; U, Y) - \max\{I(U; Y_r) - I(U; Y), 0\}.$$

When Y = (Y', Y'') consists of two components and the channel $P_{Y|X,X_r,Y_r} = P_{Y'|X,Y_r}P_{Y''|X_r}$ can be decomposed into two orthogonal components: one-shot version of the **primitive relay channel**.

Corollary

For any P_X , P_{X_r} , $P_{U'|Y_r}$, there is a deterministic coding scheme for the one-shot primitive relay channel with $M \sim \mathrm{Unif}[L]$ such that

$$P_{\theta} \leq \textbf{E} \Big[min \Big\{ \left(ln(|\mathcal{U}'||\mathcal{X}_{\mathrm{r}}|) + 1 \right) L2^{-\iota(X;\mathcal{U}',Y')} \big(2^{-\iota(X_{\mathrm{r}};Y'') + \iota(\mathcal{U}';Y_{\mathrm{r}}|Y')} + 1 \big), 1 \Big\} \Big],$$

$$(X, Y_r, U', Y') \sim P_X P_{Y_r|X} P_{U'|Y_r} P_{Y'|X,Y_r}$$
 independent of $(X_r, Y'') \sim P_{X_r} P_{Y''|X_r}$.

- $C_r = \max_{P_{X_r}} I(X_r; Y'')$ is the capacity of channel $P_{Y''|X_r}$, then the asymptotic achievable rate is $R \le I(X; U', Y') \max\{I(U'; Y_r|Y') C_r, 0\}$.
- It implies the compress-forward bound^a.

^aKim, Young-Han. "Coding techniques for primitive relay channels."In Proc. Forty-Fifth Annual Allerton Conf. Commun., Contr. Comput, p. 2007. 2007.

Partial-Decode-and-Forward Bound

- Split the message: $M \sim \text{Unif}[L] \Rightarrow M_1 \sim \text{Unif}[J], M_2 \sim \text{Unif}[L/J].$
- Node 1 sees $Y_1 = M_1$, outputs $X_1 = V$, and has an auxiliary $U_1 = (M_1, V)$
- Node 2 sees $Y_2 = (M_1, M_2, V)$, outputs $X_2 = X$, and $U_2 = (M_1, M_2, X)$.
- Relay sees $Y_3 = Y_r$, decodes U_1 , outputs $X_3 = X_r$, and $U_3 = (M_1, U)$.
- Decoder sees $Y_4 = Y$ and uses the decoding order " U_2, U_3 ?".

Corollary

Background

Fix any $P_{X,V}$, $P_{U|Y_r,V}$, function $x_r(y_r,u,v)$, and J which is a factor of L. There exists a deterministic coding scheme for the one-shot relay channel with

$$\begin{split} P_{e} & \leq \textbf{E} \Big[\min \Big\{ J 2^{-\iota(V;Y_{r})} + \big(ln(J|\mathcal{U}|) + 1 \big) (ln(J|\mathcal{V}|) + 1 \big) L J^{-1} 2^{-\iota(X;\mathcal{U},Y|\mathcal{V})} \\ & \cdot \big(2^{-\iota(\mathcal{U};V,Y) + \iota(\mathcal{U};V,Y_{r})} + 1 \big) \big(J 2^{-\iota(V;Y)} + 1 \big), 1 \Big\} \Big], \end{split}$$

where $(X, V, Y_r, U, X_r, Y) \sim P_{X,V} P_{Y_r|X,V} P_{U|Y_r,V} \delta_{X_r(Y_r,U,V)} P_{Y|X,Y_r,X_r}$.

Acyclic discrete network (ADN)

- N nodes labelled by 1,..., N.
 - Node i observes Y_i ∈ Y_i and produces X_i ∈ X_i.
 - Y_i can depend on all previous inputs and outputs X^{i-1} , Y^{i-1} .
 - ADN: a collection of channels $(P_{Y_i|X^{i-1},Y^{i-1}})_{i\in[N]}$, where $P_{Y_i|X^{i-1},Y^{i-1}}$ is a conditional distribution from $\prod_{i=1}^{i-1} \mathcal{X}_j \times \prod_{i=1}^{i-1} \mathcal{Y}_j$ to \mathcal{Y}_i .

(a)
$$Y_1 \longrightarrow \boxed{\text{Node 1}} \xrightarrow{X_1} P_{Y_2|X_1} \xrightarrow{Y_2} \boxed{\text{Node 2}} \longrightarrow X_2$$

(b)
$$Y_1 \longrightarrow \boxed{\text{Node 1}} \xrightarrow{X_1 = Y_2} \boxed{\text{Node 2}} \longrightarrow X_2 = \widehat{Y}_1$$

Figura 1: (a) Channel coding. (b) Source coding.

Coding scheme

Background



Public-randomness coding scheme

A pair $(P_W, (f_i)_{i \in [N]})$, where P_W is the distribution of the public randomness $W \in \mathcal{W}$ available to all nodes and $f_i : \mathcal{Y}_i \times \mathcal{W} \to \mathcal{X}_i$ is the encoding function of node i mapping its observation Y_i and the public randomness W to its output X_i . The operations are as follows. First, generate $W \sim P_W$. For $i = 1, \dots, N$, generate \tilde{Y}_i conditional on \tilde{X}^{i-1} , \tilde{Y}^{i-1} according to $P_{Y_i|X^{i-1}|Y^{i-1}}$, and take $\tilde{X}_i = f_i(\tilde{Y}_i, W).$

Deterministic coding scheme

A sequence of encoding functions $(f_i)_{i \in [N]}$, where $f_i : \mathcal{Y}_i \to \mathcal{X}_i$. For $i = 1, \dots, N$, the following operations are performed:

- **Noisy channel.** The output \tilde{Y}_i is generated conditional on \tilde{X}^{i-1} , \tilde{Y}^{i-1} according to $P_{Y_i|X^{i-1},Y^{i-1}}$. For $i=1, \tilde{Y}_1 \sim P_{Y_1}$ can be regarded as a source or a channel state.
- **Node operation.** Node *i* observes \tilde{Y}_i and outputs $\tilde{X}_i = f_i(\tilde{Y}_i)$.

Background



Achievability

• \tilde{X}_i , \tilde{Y}_i denote the actual random variables from the coding scheme.

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- X_i , Y_i denote the random variables following an ideal distribution.
- The goal (the "achievability") is to make the actual joint distribution $P_{\tilde{X}^N \tilde{Y}^N}$ "approximately as good as" the ideal joint distribution P_{X^N,Y^N} . For an "error set" $\mathcal{E} \subseteq (\prod_{i=1}^N \mathcal{X}_i) \times (\prod_{i=1}^N \mathcal{Y}_i)$ that we do not want $(\tilde{X}^N, \tilde{Y}^N)$ to fall into, we want

$$\mathbf{P}((\tilde{X}^N, \tilde{Y}^N) \in \mathcal{E}) \lesssim \mathbf{P}((X^N, Y^N) \in \mathcal{E}),$$

which can be guaranteed by $P_{\tilde{X}^N,\tilde{Y}^N}$ being close to P_{X^N,Y^N} in TV distance.

Theorem

Background

Fix any ADN $(P_{Y_i|X^{i-1},Y^{i-1}})_{i\in[N]}$. For any collection of indices $(a_{i,j})_{i\in[N],j\in[d_i]}$ where $(a_{i,i})_{i \in [d:]}$ is a sequence of distinct indices in [i-1] for each i, any sequence $(d'_i)_{i \in [N]}$ with $0 \le d'_i \le d_i$ and any collection of conditional distributions $(P_{U_i|Y_i,\overline{U}_i'},P_{X_i|Y_i,U_i,\overline{U}_i'})_{i\in[N]}$ (where $\overline{U}_{i,\mathcal{S}}:=(U_{a_{i,i}})_{j\in\mathcal{S}}$ for $\mathcal{S}\subseteq[d_i]$ and $\overline{U}'_i := \overline{U}_{i,[d']}$), which induces the joint distribution of X^N, Y^N, U^N (the "ideal distribution"), there exists a public-randomness coding scheme $(P_W, (f_i)_{i \in IM})$ such that the joint distribution of \tilde{X}^N , \tilde{Y}^N induced by the scheme satisfies

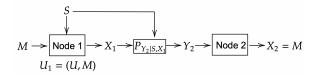
$$\delta_{\mathrm{TV}}\big(P_{X^N,Y^N},\,P_{\tilde{X}^N,\tilde{Y}^N}\big) \leq \mathbf{E}\bigg[\min\bigg\{\sum_{i=1}^N\sum_{j=1}^{d_i^r}B_{i,j},\,1\bigg\}\bigg],$$

where
$$\gamma_{i,j} := \prod_{k=j+1}^{d_i} \left(\ln |\mathcal{U}_{a_{i,k}}| + 1 \right)$$
 and

$$B_{i,j} := \gamma_{i,j} \prod_{k=i}^{d_i} \left(2^{-\iota(\overline{U}_{i,k}; \overline{U}_{i,[d_j]\setminus [j...k]}, Y_j) + \iota(\overline{U}_{i,k}; \overline{U}'_{a_{i,k}}, Y_{a_{i,k}})} + \mathbf{1}\{k > j\} \right).$$

ADN: Gelfand-Pinsker Problem





Gelfand-Pinsker Problem

- $Y_1 := (M, S), Y_2 := Y, P_{Y_2|Y_1,X_1}$ be $P_{Y|S,X}$, and $X_2 := M$.
- The auxiliary of node 1 is $U_1 = (U, M)$ for some U following $P_{U|S}$ given S.
- The decoding order of node 2 is " U_1 " (i.e., it only wants U_1).

Corollary

Background

Fix $P_{U|S}$ and function $x: \mathcal{U} \times \mathcal{S} \to \mathcal{X}$. There exists a deterministic coding scheme for the channel $P_{Y|X,S}$ with $S \sim P_S$, $M \sim \text{Unif}[L]$ such that

$$P_{e} \leq \mathbf{E} \big[\min \big\{ L2^{-\iota(U;Y)+\iota(U;S)}, 1 \big\} \big],$$

where $S, U, X, Y \sim P_S P_{U|S} \delta_{x(U,S)} P_{Y|X,S}$.

ADN: Wyner-Ziv Problem and Coding for Computing



$$Y_1 = X \longrightarrow \boxed{\text{Node 1}} \longrightarrow X_1 = M \longrightarrow \boxed{\text{Node 2}} \longrightarrow X_2 = Z$$

$$U_1 = (U, M)$$

Corollary

Fix $P_{U|X}$ and function $z: \mathcal{U} \times \mathcal{Y} \to \mathcal{Z}$. There exists a coding scheme s.t.

$$P_{\theta} \leq \mathbf{E} \Big[\min \Big\{ \mathbf{1} \{ d(X, Z) > D \} + L^{-1} 2^{-\iota(U; T) + \iota(U; X)}, 1 \Big\} \Big],$$

where $X, Y, U, Z \sim P_X P_{Y|X} P_{U|X} \delta_{z(U,Y)}$.

- Reduced to lossy source coding by $T = \emptyset$: let U = Z, then $P_e \leq \mathbf{P}(d(X,Z) > D) + \mathbf{E} \left[\min \left\{ \mathsf{L}^{-1} 2^{\iota(Z;X)}, 1 \right\} \right]$.
- Coding for computing: node 2 recovers a function f(X, T), $P_e \leq \mathbf{E}[\min\{\mathbf{1}\{d(f(X, T), Z) > \mathsf{D}\} + \mathsf{L}^{-1}2^{-\iota(U;T)+\iota(U;X)}, 1\}].$

ADN: Multiple Access Channel



Multiple Access Channel

- For j = 1, 2, two independent messages $M_i \sim \text{Unif}[L_i]$ are encoded to X_i . The decoder observes the output of $P_{Y|X_1,X_2}$ and produces (\hat{M}_1,\hat{M}_2) .
- ADN: $Y_1 := M_1, Y_2 := M_2, Y_3 := Y \text{ and } X_3 := (M_1, M_2).$
- Auxiliaries: $U_1 := (X_1, M_1)$ and $U_2 := (X_2, M_2)$.
- Decoding order of node 3: " U_2 , U_1 " (i.e., decode U_1 (soft), and then U_2 (unique), and then U_1 (unique)).

Corollary

Background

Fix P_{X_1} , P_{X_2} . There exists a deterministic coding scheme for the multiple access channel $P_{Y|X_1,X_2}$ with

$$P_e \leq \textbf{E} \Big[\min \Big\{ \gamma L_1 L_2 2^{-\iota(X_1,X_2;Y)} + \gamma L_2 2^{-\iota(X_2;Y|X_1)} + L_1 2^{-\iota(X_1;Y|X_2)}, 1 \Big\} \Big],$$

where $\gamma := \ln(L_1|\mathcal{X}_1|) + 1$, $(X_1, X_2, Y) \sim P_{X_1} P_{X_2} P_{Y|X_1|X_2}$.

Asymptotic region: $R_1 < I(X_1; Y|X_2), R_2 < I(X_2; Y|X_1), R_1 + R_2 < I(X_1, X_2; Y).$

Summary



Summary

- We provide a unified one-shot coding framework for communication and compression over general noisy networks.
- We design a proof technique "exponential process refinement lemma" that can keep track of a large number of auxiliary random variables.
- We provide novel one-shot results for various multi-hop settings.
- We recover most of the best-known one-shot results of different settings.

Future Directions

- Continuous case of the current framework.
- One-shot versions of other asymptotic bounds for relay channels.
- A unified coding scheme is useful to design automated theorem proving tools, e.g., PSITIP^a. Extensions to one-shot results is left for future study.

^aLi, Cheuk Ting. "An automated theorem proving framework for information-theoretic results."IEEE Transactions on Information Theory (2023).