## Towards an Algebraic Network Information Theory

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Joint work with Sung Hoon Lim (EPFL), Chen Feng (UBC), and Michael Gastpar (EPFL).

DIMACS Workshop on Network Coding: The Next 15 Years
December 17th, 2015

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- State-of-the-art elegantly captured in the recent textbook of El Gamal and Kim.
- Codes with algebraic structure are sought after to mimic the performance of random i.i.d. codes.


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This Talk: We build on previous work and propose a joint typicality approach to algebraic network information theory.

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- What about the " $1+$ "? Still open! (Ice wine problem.)


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- Nazer-Cadambe-Ntranos-Caire '15: Expanded compute-and-forward framework to link unequal power setting to finite fields.


## Point-to-Point Channels



- Messages: $m \in\left[2^{n R}\right] \triangleq\left\{0, \ldots, 2^{n R}-1\right\}$
- Encoder: a mapping $x^{n}(m) \in \mathcal{X}^{n}$ for each $m \in\left[2^{n R}\right]$
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## Theorem (Shannon '48)

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- Proof relies on random i.i.d. codebooks combined with joint typicality decoding.

- Codewords are independent of one another.
- Can directly target an input distribution $p_{X}(x)$.

Point-to-Point Channels: Linear Codes


Code Construction:

Point-to-Point Channels: Linear Codes


## Code Construction:

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- Channel input at time $i$ is $x_{i}(m)=x\left(u_{i}(m)\right)$.


Random Linear Codes

- Codewords are pairwise independent of one another.
- Codewords are uniformly distributed over $\mathbb{F}_{\mathrm{q}}^{n}$.

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- Basic idea: Generate many codewords to represent one message. Search in this "bin" to find a codeword with the desired type, i.e., multicoding.

Point-to-Point Channels: Linear Codes + Multicoding


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- Linear codewords: $u^{n}(m, l)=[\boldsymbol{\nu}(m) \boldsymbol{\nu}(l)] \mathrm{G} \oplus d^{n}$.

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Encoding:

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## Decoding:

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## Decoding:

- Joint Typicality Decoding: Find the unique index $\hat{m}$ such that $\left(u^{n}(\hat{m}, \hat{l}), y^{n}\right) \in \mathcal{T}_{\epsilon}^{(n)}(U, Y)$ for some index $\hat{l}$.

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- Succeeds w.h.p. if $R+\hat{R}<I(U ; Y)+D\left(p_{U} \| p_{\mathbf{q}}\right)$

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## Theorem (Padakandla-Pradhan '13)

Any rate $R$ satisfying

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is achievable. This is equal to the capacity if $q \geq|\mathcal{X}|$.

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- Next, let's examine a two-transmitter, one-receiver "compute-and-forward" network.


## Nested Linear Coding Architecture



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- Messages $m_{k} \in\left[2^{n R_{k}}\right]$ and auxiliary indices $l_{k} \in\left[2^{n \hat{R}_{k}}\right], k=1,2$.


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Nested Linear Coding Architecture


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$$
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$$

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$$
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## Nested Linear Coding Architecture



Encoding:

## Nested Linear Coding Architecture



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- Fix $p\left(u_{1}\right), p\left(u_{2}\right), x_{1}\left(u_{1}\right)$, and $x_{2}\left(u_{2}\right)$.


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## Encoding:

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- For $m_{k} \in\left[2^{n R_{k}}\right], l_{k} \in\left[2^{n \hat{R}_{k}}\right]$, the linear combination of codewords with coefficient vector a is

$$
\begin{aligned}
& a_{1} u_{1}^{n}\left(m_{1}, l_{1}\right) \oplus a_{2} u_{2}^{n}\left(m_{2}, l_{2}\right) \\
& =\left[a_{1} \boldsymbol{\eta}\left(m_{1}, l_{1}\right) \oplus a_{2} \boldsymbol{\eta}\left(m_{2}, l_{2}\right)\right] \mathbf{G} \oplus a_{1} d_{1}^{n} \oplus a_{2} d_{2}^{n} \\
& =\boldsymbol{\nu}(t) \mathbf{G} \oplus d_{w}^{n} \\
& =w^{n}(t), \quad t \in\left[2^{n \max \left\{R_{1}+\hat{R}_{1}, R_{2}+\hat{R}_{2}\right\}}\right]
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$$

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- A rate pair is achievable if there exists a sequence of codes such that $\mathrm{P}_{\epsilon}^{(n)} \rightarrow 0$ as $n \rightarrow \infty$.


## Nested Linear Coding Architecture



## Decoding:

- Joint Typicality Decoding: Find an index $t \in\left[2^{n \max \left(R_{1}+\hat{R}_{1}, R_{2}+\hat{R}_{2}\right)}\right]$ such that $\left(w^{n}(t), y^{n}\right) \in \mathcal{T}_{\epsilon}^{(n)}$.


## Nested Linear Coding Architecture



## Theorem (Lim-Chen-Nazer-Gastpar Allerton '15)

A rate pair $\left(R_{1}, R_{2}\right)$ is achievable if

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\begin{aligned}
& R_{1}<I(W ; Y)-I\left(W ; U_{2}\right), \\
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for some $p\left(u_{1}\right) p\left(u_{2}\right)$ and functions $x_{1}\left(u_{1}\right), x_{2}\left(u_{2}\right)$, where $\mathcal{U}_{k}=\mathbb{F}_{\mathbf{q}}$, $k=1,2$, and $W=a_{1} U_{1} \oplus a_{2} U_{2}$.

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- Padakandla-Pradhan '13: Special case where $R_{1}=R_{2}$.


## Proof Sketch

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$$
\begin{aligned}
& R_{k}+\hat{R}_{k}+\hat{R}_{1}+\hat{R}_{2} \\
& \quad<I(W ; Y)+D\left(p_{W} \| p_{\mathbf{q}}\right)+D\left(p_{U_{1}} \| p_{\mathbf{q}}\right)+D\left(p_{U_{2}} \| p_{\mathbf{q}}\right)
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## Theorem (Nazer-Gastpar '11)

For any channel vector $\mathbf{h}$ and integer coefficient vector $\mathbf{a}$, any rate tuple satisfying $R_{k}<R_{\text {comp }}(\mathbf{h}, \mathbf{a})$ for $k$ s.t. $a_{k} \neq 0$ is achievable where

$$
R_{\text {comp }}(\mathbf{h}, \mathbf{a})=\frac{1}{2} \log ^{+}\left(\frac{P}{\mathbf{a}^{\top}\left(P^{-1} \mathbf{I}+\mathbf{h h}^{\top}\right)^{-1} \mathbf{a}}\right)
$$

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- What about jointly decoding the linear combinations?
- Ordentlich-Erez '13 derived bounds for lattice-based codes.
- This talk: We can analyze this via joint typicality decoding to get an achievable rate region.


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\begin{aligned}
& W_{1}^{n}\left(T_{1}\right)=\bigoplus_{k=1}^{K} a_{1 k} u_{k}^{n}\left(M_{k}, L_{k}\right) \\
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with vanishing probability of error.

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- Key Technical Issue: Random linear codewords are pairwise independent, but not 4 -wise independent!


## Jointly Decoding Two Linear Combinations of $K$ Codewords

## Theorem (Lim-Chen-Nazer-Gastpar Allerton '15)

A rate tuple $\left(R_{1}, \ldots, R_{K}\right)$ is achievable for computing two linear combinations if

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& R_{k}<\min \left\{H\left(U_{k}\right)-H(V \mid Y), H\left(U_{k}\right)-H\left(W_{1}, W_{2} \mid Y, V\right)\right\}, \quad k \in \mathcal{K}_{1} \\
& R_{j}<I\left(W_{2} ; Y, W_{1}\right)-H\left(W_{2}\right)+H\left(U_{j}\right), \quad j \in \mathcal{K}_{2} \\
& R_{k}+R_{j}<I\left(W_{1}, W_{2} ; Y\right)-H\left(W_{1}, W_{2}\right)+H\left(U_{k}\right)+H\left(U_{j}\right), \quad k \in \mathcal{K}_{1}, j \in \mathcal{K}_{2} \\
& \text { or } \\
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& R_{j}<\min \left\{H\left(U_{j}\right)-H(V \mid Y), H\left(U_{j}\right)-H\left(W_{1}, W_{2} \mid Y, V\right)\right\}, \quad j \in \mathcal{K}_{2} \\
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for some $\prod_{k=1}^{K} p\left(u_{k}\right)$ and $x_{k}\left(u_{k}\right)$ and non-zero vector $\boldsymbol{b} \in \mathbb{F}_{\mathbf{q}}^{2}$, where $\mathcal{K}_{j}=\left\{k \in[1: K]: a_{j k} \neq 0\right\}, j=1,2$ and $V=b_{1} W_{1} \oplus b_{2} W_{2}$.

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for some $\prod_{k=1}^{K} p\left(u_{k}\right)$ and $x_{k}\left(u_{k}\right)$ and non-zero vector $\boldsymbol{b} \in \mathbb{F}_{\mathbf{q}}^{2}$, where $\mathcal{K}_{j}=\left\{k \in[1: K]: a_{j k} \neq 0\right\}, j=1,2$ and $V=b_{1} W_{1} \oplus b_{2} W_{2}$.

- The auxiliary linear combination $V$ plays a key role in classifying dependent competing pairs in the error analysis.


## Multiple-Access via Nested Linear Codes

## Theorem (Lim-Chen-Nazer-Gastpar Allerton '15)

A rate pair $\left(R_{1}, R_{2}\right)$ is achievable for the discrete memoryless multiple-access channel if

$$
\begin{aligned}
& \qquad \quad R_{1}<\max _{\mathbf{a} \neq \mathbf{0}} \min \left\{H\left(U_{1}\right)-H(W \mid Y), H\left(U_{1}\right)-H\left(U_{1}, U_{2} \mid Y, W\right)\right\}, \\
& \quad R_{2}<I\left(X_{2} ; Y \mid X_{1}\right), \\
& R_{1}+R_{2}<I\left(X_{1}, X_{2} ; Y\right), \\
& \quad R_{1}<I\left(X_{1} ; Y \mid X_{2}\right), \\
& R_{2}<\max _{\mathbf{a} \neq 0} \min \left\{H\left(U_{2}\right)-H(W \mid Y), H\left(U_{2}\right)-H\left(U_{1}, U_{2} \mid Y, W\right)\right\}, \\
& R_{1}+R_{2}<I\left(X_{1}, X_{2} ; Y\right) \\
& \text { for some } p\left(u_{1}\right) p\left(u_{2}\right) \text { and } x_{1}\left(u_{1}\right), x_{2}\left(u_{2}\right), \text { where } W=a_{1} U_{1} \oplus a_{2} U_{2} .
\end{aligned}
$$

Multiple-Access Rate Region

where $I_{1}=\max _{\mathbf{a} \neq \mathbf{0}} \min \left\{H\left(U_{1}\right)-H(W \mid Y), H\left(U_{1}\right)-H\left(U_{1}, U_{2} \mid Y, W\right)\right\}$

## Multiple-Access Rate Region


where $I_{2}=\max _{\mathbf{a} \neq \mathbf{0}} \min \left\{H\left(U_{2}\right)-H(W \mid Y), H\left(U_{2}\right)-H\left(U_{1}, U_{2} \mid Y, W\right)\right\}$

## Multiple-Access Rate Region



- Multiple-access rate region via nested linear codes:

$$
\mathscr{R}_{1} \cup \mathscr{R}_{2}
$$



- Even if the receiver is only interested in recovering one linear combination it can sometimes help to decode two!

MAC Capacity Region
"Two Help One"


- Even if the receiver is only interested in recovering one linear combination it can sometimes help to decode two!

Decode One Linear Combination
"Two Help One"


- Even if the receiver is only interested in recovering one linear combination it can sometimes help to decode two!

Multiple-Access via Nested Linear Codes


## Case Study: Two-Sender, Two-Receiver Network



Case Study: Two-Sender, Two-Receiver Network


Case Study: Two-Sender, Two-Receiver Network


## Case Study: Two-Sender, Two-Receiver Network



Case Study: Two-Sender, Two-Receiver Network


## Concluding Remarks

- First steps towards bringing algebraic network information theory back into the realm of joint typicality.
- Joint decoding rate region for compute-and-forward that outperforms parallel and successive decoding.

