

Algebraic Codes for Random Linear Network Coding

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Outline

Introduction

- Random Linear Network Coding
- Error control codes for RLNC
- Overview of Results

Rank Metric Codes

- Rank Metric Codes

CDCs and Subspace Codes

- DEP of CDCs
- Packing Properties
- Covering Properties

Conclusion and Future Work



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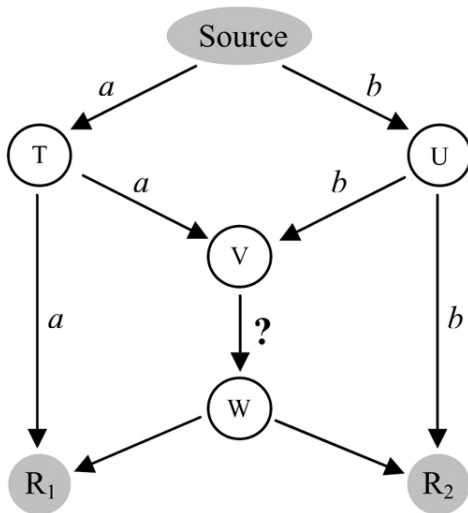
Conclusion and Future Work



Network coding

- Traditional routing: store and forward.
Does not achieve the highest throughput for multicast
- Network coding allows intermediate nodes to combine packets
- Only perform linear combinations of packets.
⇒ Linear network coding
- Results in higher throughput for multicast, robustness, and adaptability

Network coding example



Random linear network coding (RLNC)

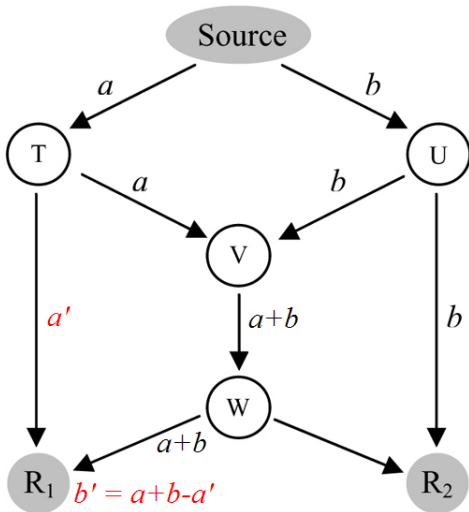
- Fixing the linear combinations requires knowledge of the network and is too rigid
- Solution: choosing linear combinations at random
- In example, 1 chance out of 3 to be successful.
However, probability of success tends to 1 with field size
- Header to keep track of linear combinations.
 $\Rightarrow (\mathbf{I}_r | \mathbf{M})$, where $\mathbf{M} = \begin{pmatrix} \mathbf{a} \\ \mathbf{b} \end{pmatrix}$
- Easy to decode: receive $(\mathbf{L} | \mathbf{LM})$, compute $\mathbf{L}^{-1}(\mathbf{LM})$



Error control for RLNC

- RLNC highly sensitive to errors
- Many types of errors
 - Link errors
 - Packet losses
 - Malfunctioning nodes
 - Adversary on the network
- Errors are highly detrimental: one packet error can corrupt all packets after linear combination

Error in network coding example



Operator channel

- RLNC preserves the row space of the input matrix.
 \Rightarrow Modeled as transmission of a linear subspace
- Two ways to modify the subspace
 - Erasure: deletion of a dimension
 - Error: addition of a dimension
- Operator channel: send U , receive

$$V = H(U) \oplus E.$$

H performs erasures, E are errors

- Error control in RLNC is a coding theory problem, where codewords are subspaces

Projective space and subspace codes

- Subspace code: set of subspaces of $\text{GF}(q)^n$.
 \Rightarrow Subset of the projective space
- Metrics:
 - subspace distance d_S for network errors
 - injection distance d_I for adversarial channels
- V obtained from U after ϵ erasures and ρ errors.

$$d_S(U, V) = \epsilon + \rho = \dim(U + V) - \dim(U \cap V)$$

$$d_I(U, V) = \max\{\epsilon, \rho\} = \max\{\dim(U), \dim(V)\} - \dim(U \cap V)$$

- For any subspace code, $d_I(\mathcal{C}) \leq d_S(\mathcal{C}) \leq 2d_I(\mathcal{C})$

Grassmannian and CDCs

- Constant-dimension code (CDC): set of subspaces of $\text{GF}(q)^n$ with dimension r .
 ⇒ Subset of the Grassmannian
- $d_S(U^\perp, V^\perp) = d_S(U, V) \Rightarrow$ assume $r \leq \frac{n}{2}$
- Advantages:
 - $d_S(\mathcal{C}) = 2d_I(\mathcal{C})$ for a CDC.
 ⇒ Versatility, and maximum d_S
 - Simplified decoding procedure
- Relation to rank metric codes through the lifting operation

Rank metric codes

- Rank metric code: set of matrices in $\text{GF}(q)^{m \times n}$
- Applications to data storage, cryptography, space-time coding
- Rank distance: $d_R(\mathbf{M}, \mathbf{N}) = \text{rk}(\mathbf{M} - \mathbf{N})$.
 $d_R(\mathbf{M}^T, \mathbf{N}^T) = d_R(\mathbf{M}, \mathbf{N}) \Rightarrow$ assume $m \geq n$
- Optimal codes: MRD codes. Gabidulin codes: RS-like MRD codes. Decoding algorithms for Gabidulin codes

Liftings of rank metric codes

- **Lifting:** $\mathbf{M} \in \text{GF}(q)^{m \times n}$, $I(\mathbf{M})$ is the row space of $(\mathbf{I}_m | \mathbf{M})$
- $d_I(I(\mathbf{M}), I(\mathbf{N})) = d_R(\mathbf{M}, \mathbf{N})$
- \mathcal{C} rank metric code in $\text{GF}(q)^{r \times (n-r)}$.
 $\Rightarrow I(\mathcal{C})$ CDC, and $d_S(I(\mathcal{C})) = 2d_I(I(\mathcal{C})) = 2d_R(\mathcal{C})$
- Error control in RLNC using liftings is a rank metric problem
- KK code: lifting of (transposed) Gabidulin code.
 Nearly optimal CDC, bounded subspace distance decoding algorithm

Overview of results

- Rank metric codes
 - Covering properties (*IT 08 + to appear in CL 09*)
 - MacWilliams identity (*EURASIP 08*)
 - DEP (*IT 08*)
 - Constant-rank codes (*submitted to IT*)
- CDCs
 - Construction and covering properties of CDCs (*submitted to IT*)
 - DEP of CDCs (*submitted to IT*)
- Subspace codes: Packing and covering properties (*submitted to IT*)

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Rank metric codes

- Sphere covering
 - Geometric properties (volumes of balls and their intersections)
 - Bounds and constructions
 - Covering radius of known codes
- MacWilliams identity
 - Polynomial form previously unknown
 - Binomial and power moments of the rank distribution
- Decoder error probability
 - Exact DEP of codes given their distance distribution
 - Upper bounds on the DEP
 - MRD codes have the highest DEP up to a scalar

CRCs

- Motivation: study CDCs and their relations to rank metric codes
- Constant-rank code (CRC): rank metric code where all codewords have the same rank
- Row space of a CRC is a CDC with related minimum distance
- Optimal CRC in $\text{GF}(q)^{m \times n}$ with rank r and $d_R = d + r$ for m large enough.
 \Rightarrow Row space: optimal CDC of length n and dimension r with $d_I = d$
- We also study CRCs. Many results for $d_R \leq r$, fewer for $d_R > r$

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DEP of CDCs

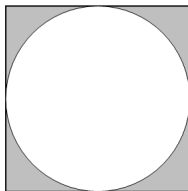
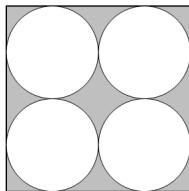
- Two decoders: bounded subspace distance, bounded injection distance
- Bounded distance decoder (BDD): finds the unique nearest codeword at distance $\leq \lfloor \frac{d-1}{2} \rfloor$
- Decoder has three outputs: success, failure, or error.
Success iff received subspace at distance $\leq \lfloor \frac{d-1}{2} \rfloor$.
Error or failure otherwise
- Error more detrimental than failure.
 \Rightarrow Focus on decoder error probability (DEP)



DEP of CDCs

- Symmetric operator channel: all subspaces after ϵ erasures and ρ errors equiprobable.
 - ⇒ Same dimension and same distance are equiprobable
- Results:
 - Exact DEP for all CDCs based on distance distribution
 - Bounds on the DEP of all liftings
 - Liftings of MRD have maximum DEP up to a scalar
- Bounded subspace distance decoder corrects more errors and has higher DEP than bounded injection decoder

Sphere packing



- How many spheres of same radius can be packed in a space?
 \Rightarrow Max cardinality of a code with a given minimum distance
 $A(d)$
- Crucial for error correcting code design

Construction of CDCs

- KK code \mathcal{E}^0 : $\mathcal{D}^0 \subseteq \text{GF}(q)^{r \times (n-r)}$ is a (transposed) Gabidulin code with $d_R = d$, where $d_S = 2d_I = 2d$.

$$E_{0,j}^0 = R(\mathbf{I}_r | \mathbf{D}_j^0)$$

- Layer \mathcal{E}^k for $1 \leq k \leq \lfloor \frac{r}{d} \rfloor$: $\mathcal{C}^k \subseteq \text{GF}(q)^{(r-kd) \times kd}$, $\mathcal{D}^k \subseteq \text{GF}(q)^{r \times (n-r-kd)}$ are (transposed) Gabidulin codes with $d_R = d$ or trivial codes.

$$E_{i,j}^k = R \left(\begin{array}{c|c|c} \mathbf{I}_{r-kd} & \mathbf{C}_i^k & \mathbf{0} \\ \hline \mathbf{0} & \mathbf{0} & \mathbf{I}_{kd} \end{array} \middle| \mathbf{D}_j^k \right)$$

- Augmented KK code $\mathcal{E} = \bigcup_{k=0}^{\lfloor \frac{r}{d} \rfloor} \mathcal{E}^k$

Augmented KK codes

- $d_I(R(\mathbf{A}), R(\mathbf{B})) \geq d_I(R(\mathbf{A}_1), R(\mathbf{B}_1))$, where $\mathbf{A}_1, \mathbf{B}_1$ are subsets of columns
 $\Rightarrow d_I = d, d_S = 2d_I = 2d$
- Properly contains a KK code. Greatest cardinality for $d < r$
- Enhanced BDD for augmented KK code:
 - Corrects more than bounded subspace distance decoder
 - Complexity on the same order as BDD of KK code

EBDD(k, \mathbf{A})

Input: k and $\mathbf{A} = (\mathbf{A}_1 | \mathbf{A}_2 | \mathbf{A}_3)$, $\mathbf{A}_1 \in \text{GF}(q)^{a \times (r-kd)}$, $\mathbf{A}_2 \in \text{GF}(q)^{a \times kd}$,
 $\mathbf{A}_3 \in \text{GF}(q)^{a \times (n-r)}$

Output: $(E_{i,j}^k, d_k, f_k)$

1. If $k = 0$, decoder of $\mathcal{E}^0 \Rightarrow E_{0,j}^0$, calculate $d_k = d_S(R(\mathbf{A}), E_{0,j}^0)$,
and return $(E_{0,j}^0, d_k, 0)$
2. Decoder of $I(\mathcal{C}^k)$ on $(\mathbf{A}_1 | \mathbf{A}_2) \Rightarrow \mathbf{C}_i^k$
3. Decoder of $I(\mathcal{D}^k)$ on $(\mathbf{A}_1 | \mathbf{A}_3) \Rightarrow \mathbf{D}_j^k$
4. Calculate $d_k = d_S(R(\mathbf{A}), E_{i,j}^k)$,
 $f_k = 2d - \max\{d_S(R(\mathbf{A}_1 | \mathbf{A}_2), I(\mathbf{C}_i^k)), d_S(R(\mathbf{A}_1 | \mathbf{A}_3), I(\mathbf{D}_j^k))\}$,
and return $(E_{i,j}^k, d_k, f_k)$

Decoder for \mathcal{E}

Input: $\mathbf{A} = (\mathbf{A}_0 | \mathbf{A}_3)$, $\mathbf{A}_0 \in \text{GF}(q)^{a \times r}$, $\mathbf{A}_3 \in \text{GF}(q)^{a \times (n-r)}$

Output: The unique nearest codeword in \mathcal{E} from $R(\mathbf{A})$ or failure

1. If $\text{rk}(\mathbf{A}) < r - d + 1$, return failure
2. Calculate $r - \text{rk}(\mathbf{A}_0) = ld + m$, with $0 \leq l \leq \lfloor \frac{r}{d} \rfloor$ and $0 \leq m < d$
3. $\text{EBDD}(l, \mathbf{A}) \Rightarrow (E_{i,j}^l, d_l, f_l)$. If $d_l \leq d - 1$, return $E_{i,j}^l$
4. If $m = 0$, return failure.
Otherwise $\text{EBDD}(l + 1, \mathbf{A}) \Rightarrow (E_{s,t}^{l+1}, d_{l+1}, f_{l+1})$.
If $d_{l+1} \leq d - 1$, return $E_{s,t}^{l+1}$
5. If $d_l < \min\{d + m, f_l, d_{l+1}, f_{l+1}, 2d - m\}$, return $E_{i,j}^l$.
If $d_{l+1} < \min\{d + m, d_l, f_l, f_{l+1}, 2d - m\}$, return $E_{s,t}^{l+1}$
6. Return failure

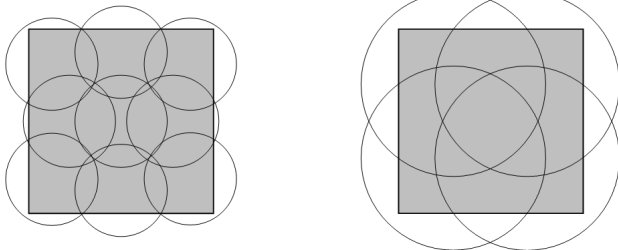
Packing properties of subspace codes

- Max cardinality of a subspace code (resp., CDC) with minimum injection distance d : $A_I(d)$ (resp., $A_C(r, d)$)
- Upper bound:

$$A_I(d) \leq \sum_r A_C(r, d) \sim A_C\left(\left\lfloor \frac{n}{2} \right\rfloor, d\right)$$

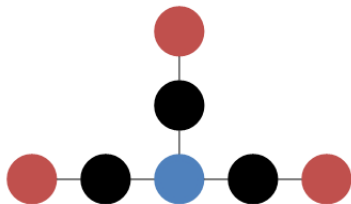
- Lower bound: $A_I(d) \geq A_C(r, d)$. Nearly tight for $r = \lfloor \frac{n}{2} \rfloor$
- Same situation for the subspace metric: $A_S(d) \sim A_C(\lfloor \frac{n}{2} \rfloor, \lceil \frac{d}{2} \rceil)$
- CDCs optimal up to a scalar for both metrics.
 \Rightarrow Nearly optimal codes in the injection metric with $d_S = 2d_I$

Sphere covering



- How many spheres needed to cover a space?
 \Rightarrow Min cardinality of a code with a given covering radius $K(\rho)$
- Applications: minimum distance decoding, decoding with erasures, data compression
- Sphere covering bound: $K(\rho) \geq \frac{|E|}{\max V(\rho)}$
- Greedy upper bound: $K(\rho) \lesssim \frac{|E|}{\min V(\rho)}$

Sphere covering example



- Sphere covering bound: $K(1) \geq \lceil \frac{7}{4} \rceil = 2$
- Greedy construction: $K(1) \leq 4$
- However, $K(1) = 3$

Covering properties of CDCs

- We study how CDCs cover the Grassmannian.
Min cardinality of a CDC with covering radius ρ : $K_C(r, \rho)$
- Volume of a ball equal for all centers.
 \Rightarrow Sphere covering bound asymptotically tight
- The Grassmannian with the injection metric is an association scheme.
Intersection of two spheres with radii u and s and distance between their centers d : $J_C(u, s, d)$
- Refinement of the sphere covering bound based on linear programming

Refined sphere covering bound for CDCs

- For $0 \leq \delta \leq \rho$, let $T_\delta = \min \sum_{i=0}^r A_i(\delta)$, subject to

$$A_i(\delta) = 0 \text{ for } 0 \leq i \leq \delta - 1,$$

$$1 \leq A_\delta(\delta) \leq N_C(\delta),$$

$$0 \leq A_i(\delta) \leq N_C(i) \text{ for } \delta + 1 \leq i \leq r,$$

$$\sum_{i=0}^r A_i(\delta) \sum_{s=0}^{\rho} J_C(l, s, i) \geq N_C(l) \text{ for } 0 \leq l \leq r.$$

Then $K_C(r, \rho) \geq \max_{0 \leq \delta \leq \rho} T_\delta$

- Proof: U subspace at distance δ from a CDC with covering radius ρ , $A_i(\delta)$ distance distribution from U

Covering with liftings

- Liftings have covering radius r . Proof: consider $R(\mathbf{0}_r | \mathbf{M})$.
 \Rightarrow Liftings are not optimal packing CDCs
- Construction of covering CDCs based on liftings.
 Min cardinality of a code with rank radius ρ : $K_{\mathbf{R}}(\rho)$
- \mathcal{C} optimal rank metric covering code.
 $L(\mathcal{C})$: all possible permutations of liftings of codewords in \mathcal{C} .
 $\Rightarrow |L(\mathcal{C})| \leq \binom{n}{r} K_{\mathbf{R}}(\rho)$
- $L(\mathcal{C})$ has covering radius ρ . Proof: all subspaces are permutations of liftings
- Asymptotically optimal but not good for finite values

Covering in the injection metric

- Min cardinality of a subspace code with injection covering radius ρ : $K_I(\rho)$
- Volume of a ball depends on the dimension of its center
- However, $V_I(r, \rho) \sim f(\rho)$.
 \Rightarrow Sphere covering bound asymptotically tight
- Construction using covering CDCs: $K_I(\rho) \leq \sum_{r=0}^n K_C(r, \rho)$.
 Asymptotically optimal

Covering in the subspace metric

- Min cardinality of a subspace code with subspace covering radius ρ : $K_S(\rho)$
- Volume of a ball depends on the dimension of its center and $V_S(r, \rho) \sim g(r, \rho)$
- Sphere covering bound, construction using CDCs: not asymptotically tight
- We derive asymptotically tight lower and upper bounds

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Conclusion and Future Work

- Summary of results
- Future work:
 - RLNC: implementation and related problems
 - Constructions of packing and covering CDCs and subspace codes
 - Connection between subspace codes and rank metric codes
 - Decoding of error control codes for RLNC

Definitions of subspace and injection metrics

$$\begin{aligned}
 d_S(U, V) &= \dim(U + V) - \dim(U \cap V) \\
 &= \dim(U) + \dim(V) - 2 \dim(U \cap V) \\
 &= 2 \dim(U + V) - \dim(U) - \dim(V)
 \end{aligned}$$

$$\begin{aligned}
 d_I(U, V) &= \frac{1}{2} d_S(U, V) + \frac{1}{2} |\dim(U) - \dim(V)| \\
 &= \max\{\dim(U), \dim(V)\} - \dim(U \cap V) \\
 &= \dim(U + V) - \min\{\dim(U), \dim(V)\}
 \end{aligned}$$

$$|\dim(U) - \dim(V)| \leq d_I(U, V) \leq d_S(U, V) \leq \dim(U) + \dim(V)$$

Injection distance of liftings

For $\mathbf{M}, \mathbf{N} \in \text{GF}(q)^{r \times (n-r)}$,

$$\begin{aligned}
 d_I(I(\mathbf{M}), I(\mathbf{N})) &= \text{rk} \left(\begin{array}{c|c} \mathbf{I}_r & \mathbf{M} \\ \hline \mathbf{I}_r & \mathbf{N} \end{array} \right) - r \\
 &= \text{rk} \left(\begin{array}{c|c} \mathbf{I}_r & \mathbf{M} \\ \hline \mathbf{0} & \mathbf{M} - \mathbf{N} \end{array} \right) - r \\
 &= \text{rk}(\mathbf{M} - \mathbf{N})
 \end{aligned}$$

CRCs

Theorem

For all $\mathbf{X}, \mathbf{Y} \in \text{GF}(q)^{m \times n}$,

$$\begin{aligned} d_I(R(\mathbf{X}), R(\mathbf{Y})) + d_I(C(\mathbf{X}), C(\mathbf{Y})) - |\text{rk}(\mathbf{X}) - \text{rk}(\mathbf{Y})| \\ \leq d_R(\mathbf{X}, \mathbf{Y}) \\ \leq \min\{d_I(R(\mathbf{X}), R(\mathbf{Y})), d_I(C(\mathbf{X}), C(\mathbf{Y}))\} + \min\{\text{rk}(\mathbf{X}), \text{rk}(\mathbf{Y})\}. \end{aligned}$$

Therefore, for a CRC \mathcal{C} :

$$d_I(R(\mathcal{C})) + d_I(C(\mathcal{C})) \leq d_R(\mathcal{C}) \leq \min\{d_I(R(\mathcal{C})), d_I(C(\mathcal{C}))\} + r.$$

Optimal CRCs

Proposition

For all q , $2 \leq d \leq r \leq n \leq m$,

$$\min\{A_C(q, n, r, d), A_C(q, m, r, r)\} \leq A_R(q, m, n, r, d+r) \leq A_C(q, n, r, d).$$

For $2r \leq n$, $A_C(q, n, r, d) \sim q^{(n-r)(r-d+1)}$, $A_C(q, m, r, r) \sim q^{m-r}$.

\Rightarrow For $m \geq (n-r)(r-d+1) + r + 1$, $A_C(q, m, r, r) \geq A_C(q, n, r, d)$

f_k

Lemma

Suppose the output of $\text{EBDD}(k, \mathbf{A})$ is $(E_{i,j}^k, d_k, f_k)$, then $d_S(R(\mathbf{A}), E_{u,v}^k) \geq f_k$ for any $E_{u,v}^k \in \mathcal{E}^k$ provided $(u, v) \neq (i, j)$.

Proof.

We have

$$f_k = \min\{2d - d_S(R(\mathbf{A}_1|\mathbf{A}_2), I(\mathbf{C}_i^k)), 2d - d_S(R(\mathbf{A}_1|\mathbf{A}_3), I(\mathbf{D}_j^k))\}.$$

When $u \neq i$,

$$\begin{aligned} d_S(R(\mathbf{A}), E_{u,v}^k) &\geq d_S(R(\mathbf{A}_1|\mathbf{A}_2), I(\mathbf{C}_u^k)) \\ &\geq d_S(I(\mathbf{C}_i^k), I(\mathbf{C}_u^k)) - d_S(R(\mathbf{A}_1|\mathbf{A}_2), I(\mathbf{C}_i^k)) \\ &\geq 2d - d_S(R(\mathbf{A}_1|\mathbf{A}_2), I(\mathbf{C}_i^k)) \geq f_k. \end{aligned}$$

Similarly, when $v \neq j$, we obtain

$$d_S(R(\mathbf{A}), E_{u,v}^k) \geq 2d - d_S(R(\mathbf{A}_1|\mathbf{A}_3), I(\mathbf{D}_j^k)) \geq f_k.$$

