

# Least Squares Superposition Codes of Moderate Dictionary Size, Reliable at Rates up to Capacity

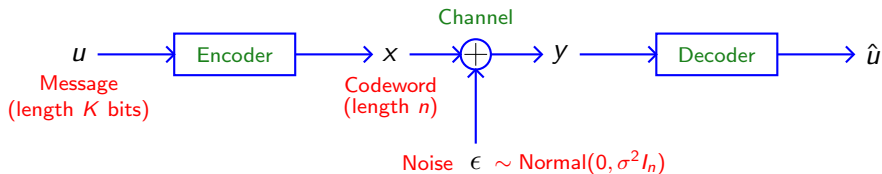
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Joint work with Andrew Barron

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- 2 Sparse Superposition Codes
- 3 Partitioned Superposition Codes
  - Encoding
  - Performance of Least Squares Decoding
- 4 Analysis of Reliability at Rates up to Capacity

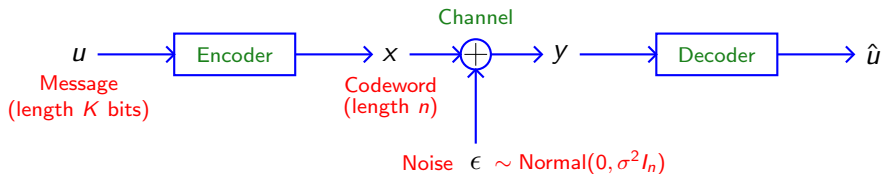
# Gaussian Channel. (Power $P$ , Noise variance $\sigma^2$ )



## Characteristics

- Power constraint:  $\text{Ave } \|x\|^2 \leq nP$
- signal-to-noise:  $\nu = P/\sigma^2$
- Capacity:  $\frac{1}{2} \log\left(1 + \frac{P}{\sigma^2}\right)$

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## Interested in

- Rate:  $R = K/n$
- $\text{Prob}\{\hat{u} \neq u\}$
- Low fraction of mistakes

## Challenges in Code construction

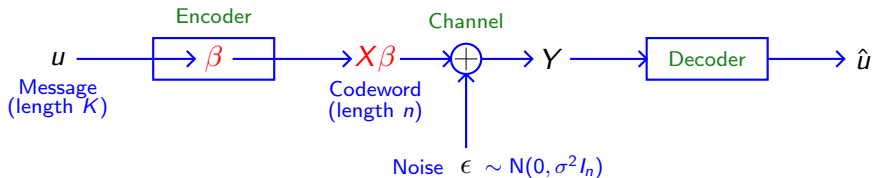
- Achieve Rate arbitrarily close to Capacity
- Good error exponents
- Manageable codebook
- Fast Encoding
- Fast Decoding

# Sparse Superposition Codes

$$\text{Model : } Y = X\beta + \epsilon$$

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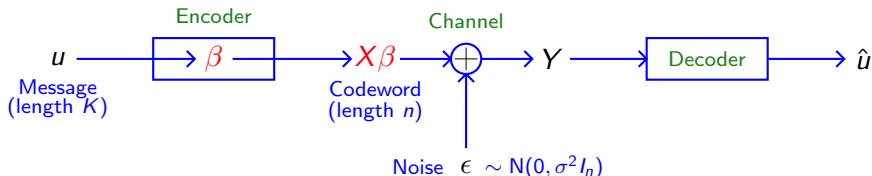


## Code design

- $n \times N$  design matrix  $X$
- Received string:  $Y = X\beta + \epsilon$
- Coefficient vector  $\beta$  is **sparse** is non-zero values

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- Coefficient vector  $\beta$  is **sparse** is non-zero values
- **Not a linear code in algebraic coding sense**



# Sparse Superposition Codes

$$X = \begin{bmatrix} \text{---} & \text{---} & \text{---} & \dots & \text{---} \end{bmatrix}$$
$$\beta = (\dots, \mathbf{1}, \dots, \mathbf{1}, \dots, \dots, \mathbf{1}, \dots)$$

## Code design

- $n \times N$  matrix  $X$  with entries independent  $\text{Normal}(0, P/L)$
- $\beta$  has exactly  $L$ , with  $L \ll N$  non-zero elements, all equal to  $\mathbf{1}$
- Average of  $\|X\beta\|^2 \leq nP$
- Codeword is the sum of the selected columns

# Partitioned Superposition Codes

$$X = \begin{bmatrix} \text{Section 1} & \text{Section 2} & \dots & \text{Section } L \\ \leftarrow B \text{ columns} \rightarrow & \leftarrow B \text{ columns} \rightarrow & & \leftarrow B \text{ columns} \rightarrow \\ \left[ \begin{array}{c} \vdots \\ \vdots \\ \vdots \end{array} \right] & \left[ \begin{array}{c} \vdots \\ \vdots \\ \vdots \end{array} \right] & \dots & \left[ \begin{array}{c} \vdots \\ \vdots \\ \vdots \end{array} \right] \end{bmatrix}$$
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## Code design

- $n \times N$  matrix  $X$  with entries independent  $\text{Normal}(0, P/L)$
- Columns of  $X$  divided into  $L$  sections of size  $B$ . So  $N = LB$
- $\beta$  has exactly **one** element non-zero in each section

# Partitioned Superposition Codes

$$X = \begin{bmatrix} \text{Section 1} & \text{Section 2} & \dots & \text{Section } L \\ \leftarrow B \text{ columns} \rightarrow & \leftarrow B \text{ columns} \rightarrow & & \leftarrow B \text{ columns} \rightarrow \\ \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \dots & \vdots \end{bmatrix}$$
$$\beta = (\dots, \mathbf{1}, \dots, \dots, \mathbf{1}, \dots, \dots, \mathbf{1}, \dots)$$

The diagram illustrates a matrix  $X$  partitioned into  $L$  sections. Each section  $i$  (labeled "Section 1", "Section 2", ..., "Section  $L$ ") contains  $B$  columns. The matrix is shown as a large square with a vertical ellipsis in the middle. The vector  $\beta$  is shown below the matrix, with a '1' in the position corresponding to the end of each section, and ellipses indicating other entries.

## Relationship: $L$ , $B$ , $n$ and $R$

- Number of codewords :  $B^L$
- Length of message string  $K = L \log_2 B$  bits
- Blocklength  $n = (1/R)L \log B$

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$$\beta = ( \dots, \mathbf{1}, \dots, \mathbf{1}, \dots )$$

0,1,.....,B-1,0,1,.....,B-1

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## Map from Message $u$ to $\beta$

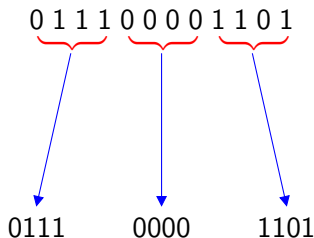
- Assume length of  $u$ ,  $K = L \log_2 B$   
For ex. take  $L = 3$  and  $\log_2 B = 4$ .

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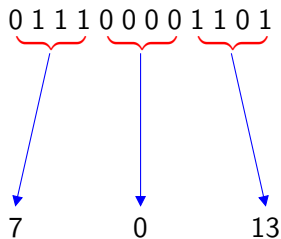
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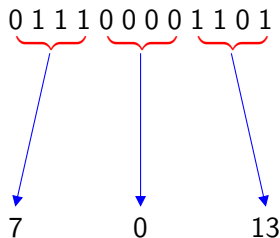
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Non-zero elements of  $\beta$ :

7<sup>th</sup> element from Section 1

0<sup>th</sup> element from Section 2

13<sup>th</sup> element from Section 3

## Map from Message $u$ to $\beta$

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For ex. take  $L = 3$  and  $\log_2 B = 4$ .
- Split  $u$  into  $L$  subtrings of  $\log_2 B$  bits
- Substrings give addresses of chosen columns
- For map :  $u \rightarrow \beta$ ,  
Choose non-zero elements of  $\beta$  in each section as given by these indices

## Least Square Decoder

- Find  $\hat{\beta}$  which **minimizes**  $\|Y - X\beta\|^2$  over  $\beta$ 's of the assumed form

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## Reliability

- Want error  $\hat{\beta} \neq \beta^*$  to have small probability, when  $\beta^*$  is sent
  - Small probability of Block error
- Less stringent, want  $\hat{\beta}$  to not equal to  $\beta^*$  in at most  $\alpha$  sections
  - Small probability that **section error rate** is greater than  $\alpha$

- Least Squares is the optimal decoder. It minimizes probability of error with uniform distribution on input strings

# Decoding, Least Squares

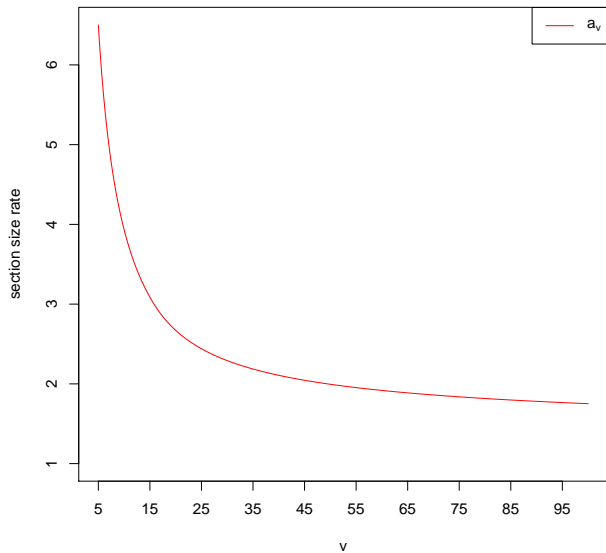
- Least Squares is the optimal decoder. It minimizes probability of error with uniform distribution on input strings
- Analysis here of performance of Least Squares, without concern for computational feasibility
- A computationally feasible algorithm discussed

Today, Session S-Fr-3, 2:40-4:00 p.m.

## Result 1: Section size

- To achieve rates up to capacity, the section size  $B$  need only be a polynomial in  $L$ .
- In particular,  $B = L^{a_v}$ , where  $a_v$  is a function of only  $v$ .
  - $a_v$  is decreasing function of  $v$
  - $a_v$  is near 1 for large  $v$
- Dictionary size  $N = L^{1+a_v}$

# Plot of $a_v$





## Result 2: Error Exponent

- Let

$$\epsilon = \text{Prob}\{\# \text{ section mistakes} > \alpha L\}$$

be the probability that more than  $\alpha$  fraction of sections are wrong.  
Then,

$$\epsilon \leq \exp\{-n c_v \min(\alpha, (C-R)^2)\}$$

where  $c_v$  is a constant that depends on only  $v$ .

## From Partially Correct to Completely Correct Decoding

- Let  $R$  be a rate for which the partitioned superposition code has

$$\text{Prob}\{\# \text{ section mistakes} > \alpha L\} = \epsilon.$$

- Then through composition with an **outer Reed-Solomon code**, one obtains a code with Rate  $R_{tot} = (1 - 2\alpha)R$  and

$$\text{Prob}\{\text{block error}\} = \epsilon$$

# Performance of Least Squares

## From Partially Correct to Completely Correct Decoding

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## Corollary 3: Block error probability

- Taking  $\alpha$  of order  $(C - R)^2$  we have

$$\text{Prob}\{\text{block error}\} \leq \exp\{-n \check{c}_v (C - R_{tot})^2\}$$

- Optimal form of exponent as in **Shannon & Gallager** or **Polyanskiy et.al**

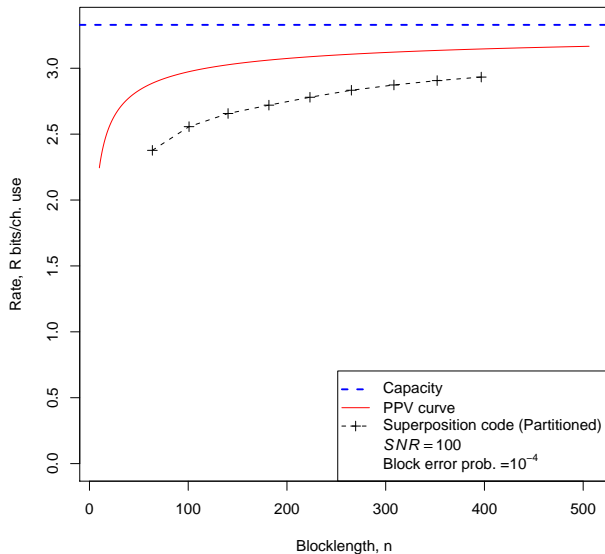
## Comparison with *PPV* curve

- Polyanskiy, Poor and Verdu demonstrate that for the Gaussian channel the following approximate relation holds for an optimal code

$$R \approx C - \sqrt{\frac{V}{n}} Q^{-1}(\epsilon) + \frac{1}{2} \frac{\log n}{n}$$

- $V = (\nu/2)(\nu + 2) \log^2 e / (\nu + 1)^2$  is the channel dispersion
- $Q = 1 - \Phi$ , where  $\Phi$  is Gaussian distribution function

# Comparison with *PPV* curve



# Superpositions for Multiple users vs our Single user channel

- Cover introduced Superposition Codes for multi-user Gaussian channels
- Codeword sent is sum of codewords for respective users
- Here we use superpositions for simplification of the single user channel

# Relationship to Sparse Signal Recovery

- **Wainwright and others:** Necessary and Sufficient conditions on  $n$  for sparsity recovery. When applied to our settings where  $N \gg L$ , these give that the  $n$  required is *constant*  $\times L \log(N/L)$
- It is natural to call (the reciprocal of) the best constant, for a given set of allowed signals and given noise distribution, the **compressed sensing capacity** or **signal recovery capacity**.
- For our setting  $n = (1/R)L \log B$  so that the best constant is  $1/C$  and thus the **signal recovery capacity** is equal to the **Shannon capacity**.

# Error Probability Bound

## Analysis

- Least squares estimate  $\hat{\beta}$  satisfies  $|Y - X\hat{\beta}|^2 \leq |Y - X\beta^*|^2$
- Error event of a fraction of  $\alpha = \ell/L$  section mistakes, contained in

$$E_\alpha = \{|Y - X\beta|^2 \leq |Y - X\beta^*|^2 \text{ for some } \beta \in \text{Wrong}_\alpha\}$$

where  $\text{Wrong}_\alpha$  is the set of  $\beta$  differing from  $\beta^*$  in fraction  $\alpha$  sections.

- Our bound:

$$\text{Prob}[E_\alpha] \leq \binom{L}{\alpha L} \exp\{-nD_\alpha\}$$

- Exponent  $D_\alpha$  is sufficiently large to cancel the combinatorial coefficient provided the  $B \geq L^{a_v}$  and  $R < C$ .



## Analysis

- Ingredients in  $D_\alpha = D(\Delta_\alpha, \rho_\alpha^2)$

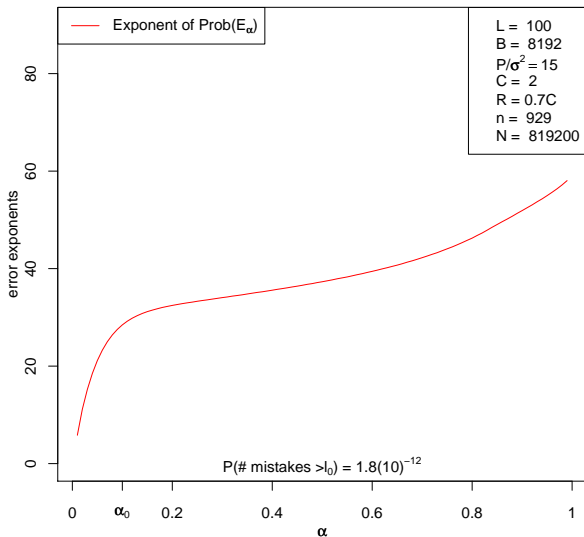
$$\Delta_\alpha = \alpha(C - R) + (C_\alpha - \alpha C)$$

$$C_\alpha = (1/2) \log(1 + \alpha v)$$

$$1 - \rho_\alpha^2 = \alpha(1 - \alpha)v / (1 + \alpha^2 v)$$

- $D(\Delta, \rho^2)$  is the cumulant generating function for  $(1/2)(Z_1^2 - Z_2^2)$  with  $Z_1, Z_2$  bivariate normal, mean zero, unit variance and correlation  $\rho$ .
  - Near  $(1/2)\Delta^2 / (1 - \rho^2)$  for small  $\Delta$

# Contributions to Error Exponent



# Summary

- Sparse superposition coding is reliable at rates up to channel capacity
- Error probability of the optimum form for  $R < C$
- Analysis blends modern statistical regression and information theory

Thank You