

# The Peeling Decoder : Theory and some Applications

Krishna R. Narayanan

Thanks to Henry Pfister, Avinash Vem, Nagaraj Thenkarai Janakiraman,  
Kannan Ramchandran, Jean-Francois Chamberland

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# Introduction

## Message passing algorithms

- Remarkably successful in coding theory
- Used to design capacity-achieving codes/decoders for a variety of channels
- Tools have been developed to analyze their performance

## Two main goals

### Goal 1

Review some developments in modern coding theory and show how to analyze the performance of a simple peeling decoder for the BEC and  $p$ -ary symmetric channels.

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Review some developments in modern coding theory and show how to analyze the performance of a simple peeling decoder for the BEC and  $p$ -ary symmetric channels.

## Goal 2

Show that the following problems have the same structure as channel coding problems and show how to use the **peeling decoder** to solve them.

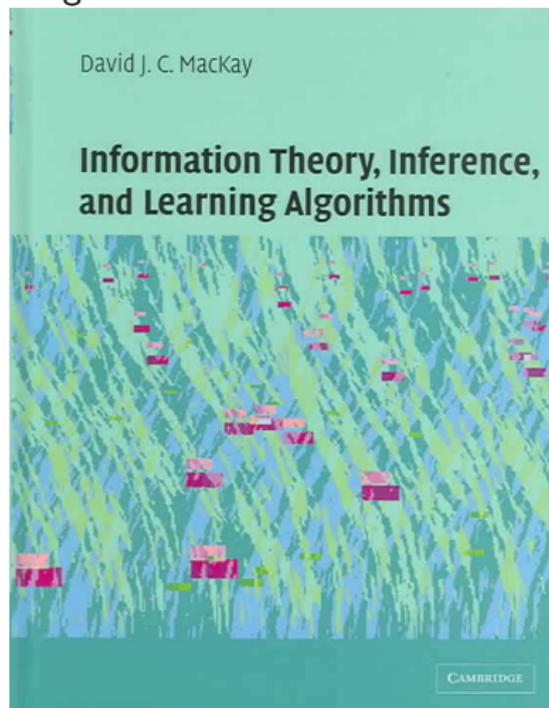
## Problems

- **Uncoordinated massive multiple access**
- **Sparse Fourier transform (SFT) computation**
- **Sparse Walsh-Hadamard transform computation**
- **Compressed sensing**
  - Data stream computing
  - Group testing
  - Compressive phase retrieval

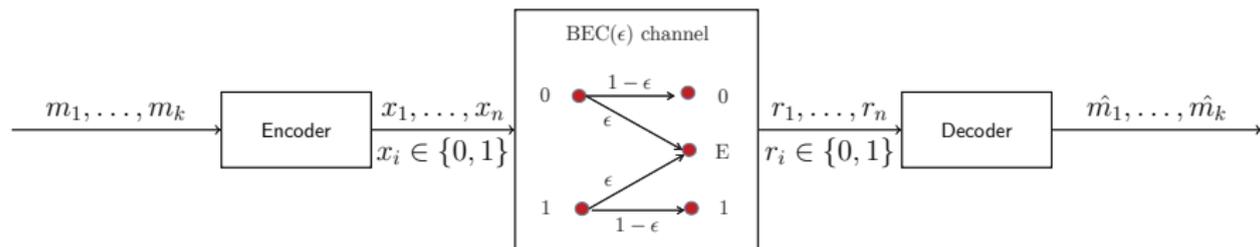


## Remembering Sir David MacKay

David Mackay's rediscovery of LDPC codes and his very interesting book on Information Theory has undoubtedly had a big influence on the field.



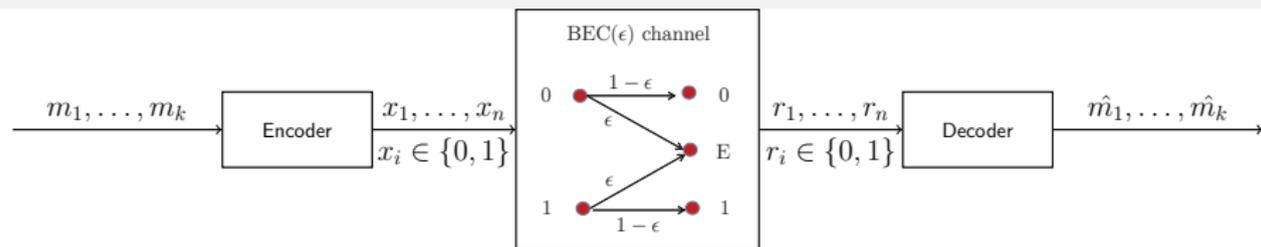
# Binary erasure channel (BEC) and erasure correction



## Channel coding problem

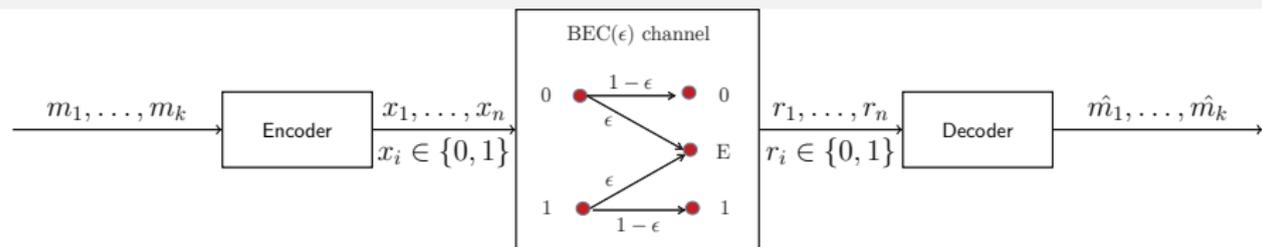
- Transmit a message  $\underline{m} = [m_1, \dots, m_k]^T$  through a binary erasure channel
- Encode the  $k$ -bit message  $\underline{m}$  into a  $n$ -bit codeword  $\underline{x}$
- Redundancy is measured in terms of rate of the code  $R = k/n$

# Binary erasure channel (BEC) and erasure correction



Capacity achieving sequence of codes

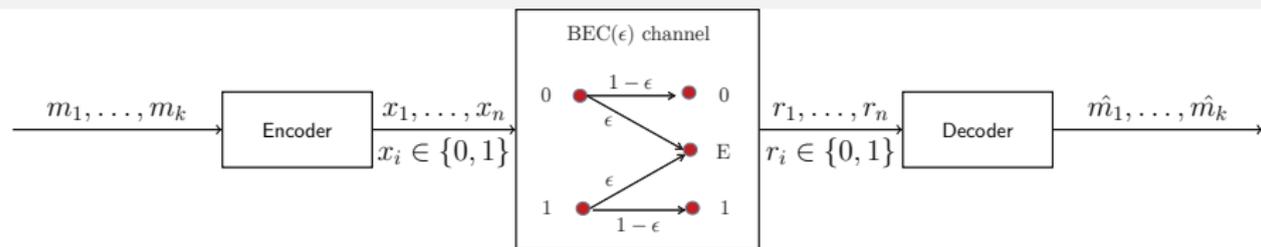
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## Capacity achieving sequence of codes

- Capacity  $C(\epsilon) = 1 - \epsilon$

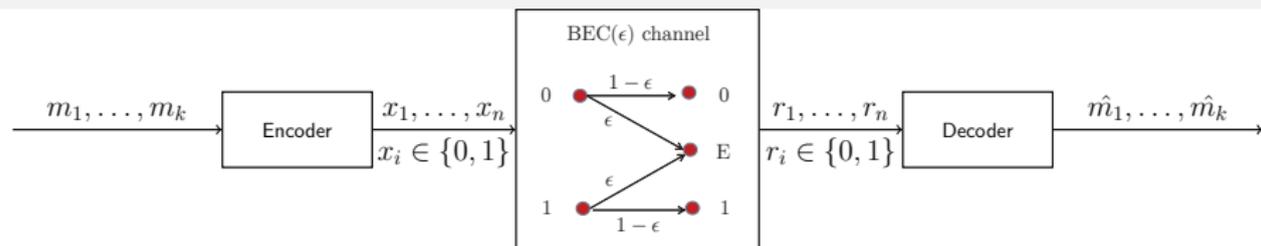
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- A sequence of codes  $\{\mathcal{C}^n\}$
- Probability of erasure  $P_e^n$
- Rate  $R^n$
- Capacity achieving if  $P_e^n \rightarrow 0$  as  $n \rightarrow \infty$  while  $R^n \rightarrow C$

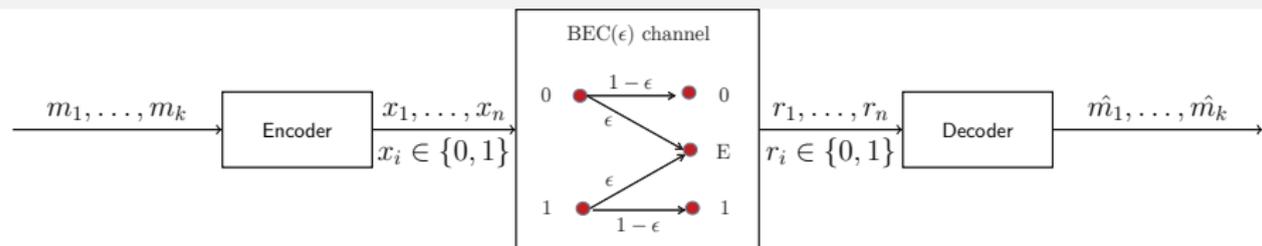
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- Find efficient encoders/decoders in terms encoding and decoding complexities

# Binary erasure channel (BEC) and erasure correction



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- **Find efficient encoders/decoders in terms encoding and decoding complexities**

## Significance of the erasure channel

- Introduced by Elias in 1954 as a toy example
- Has become the canonical model for coding theorists to gain insight

## $(n, k)$ Binary linear block codes - basics

$\mathbf{G}$  is a  $n \times k$  generator matrix

$$\begin{bmatrix} g_{1,1} & \cdots & g_{k,1} \\ \vdots & \ddots & \vdots \\ \vdots & \ddots & \vdots \\ g_{n,1} & & g_{k,n} \end{bmatrix} \begin{bmatrix} m_1 \\ \vdots \\ m_k \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

Example - (6,3) code

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}$$

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Parity check matrix -  $\mathbf{H}$  is a  $(n - k) \times n$  matrix s.t.  $\mathbf{H}\mathbf{G} = \mathbf{0} \Rightarrow \mathbf{H}\underline{x} = \mathbf{0}$

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

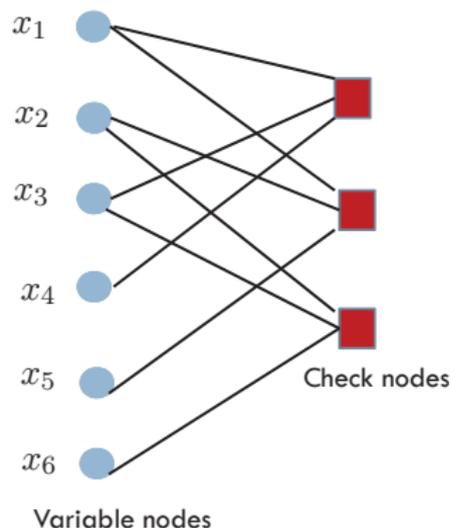
# Tanner graph representation of codes

$$H = \begin{matrix} & x_1, x_2, x_3, x_4, x_5, x_6 \\ \begin{bmatrix} 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

$$x_1 \oplus x_3 \oplus x_4 = 0$$

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- Gallager'63, Tanner'81
- Parity check matrix implies that  $\mathbf{H}\underline{x} = 0$
- Code constraints can be specified in terms of a bipartite (Tanner) graph

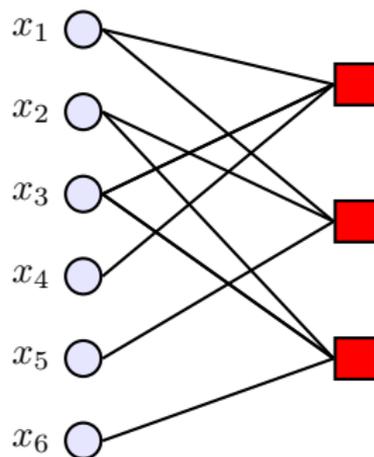
## Peeling decoder for the BEC

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Tanner Graph

- Zyablov and Pinsker'74, Luby et al '95
- Remove edges incident on known variable nodes and adjust check node values
- If there is a check node with a **single edge**, it can be recovered

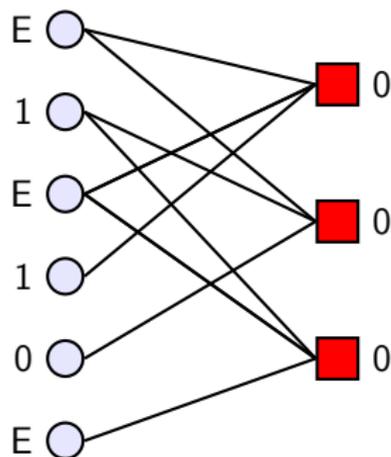
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Received block

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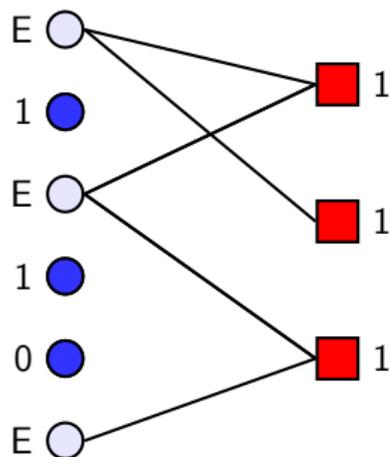
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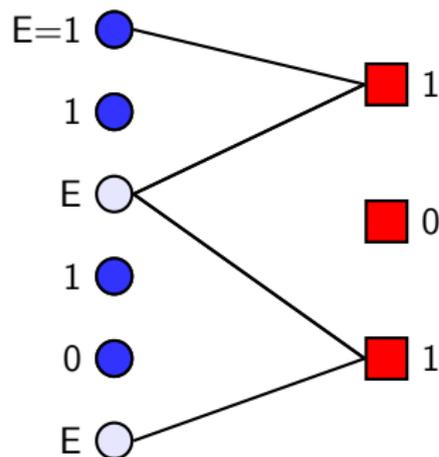
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Peeling Step 2

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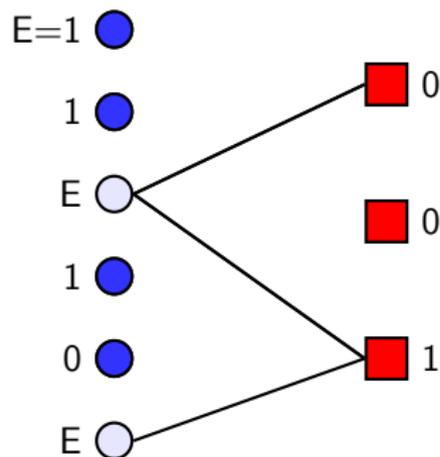
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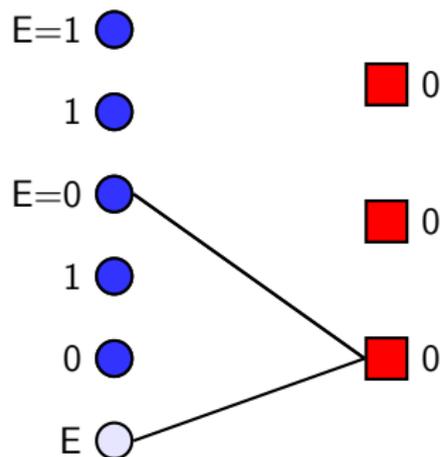
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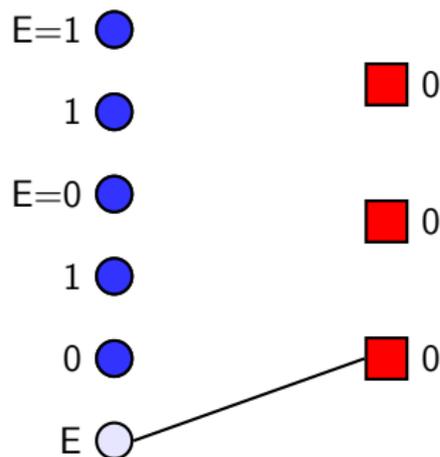
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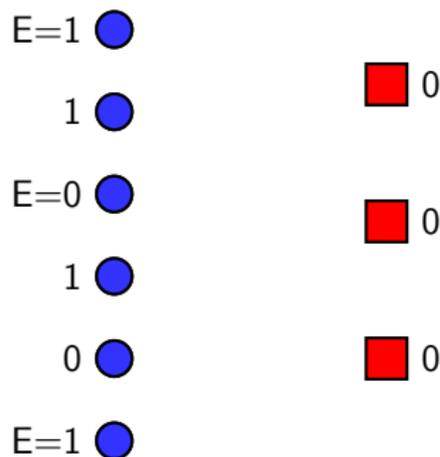
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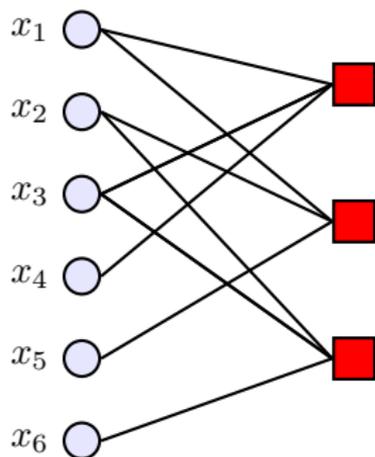
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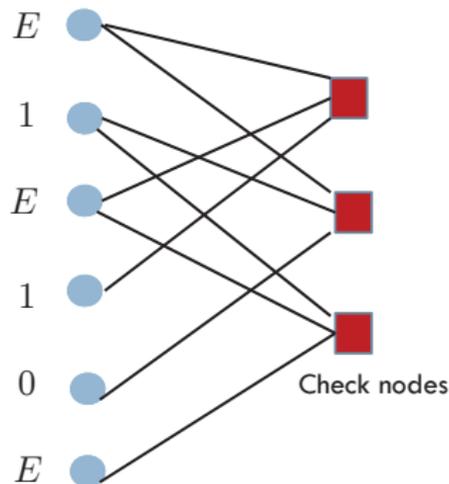
Peeling Step 4

- Zyablov and Pinsker'74, Luby et al '95
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## Message passing decoder for the BEC



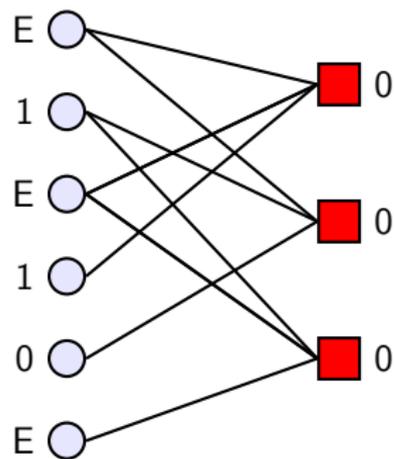
Tanner Graph



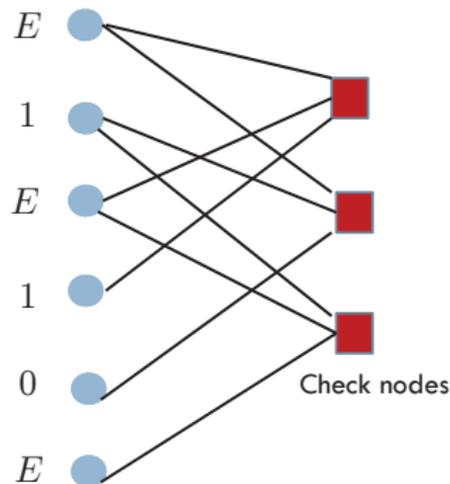
Variable nodes

- Pass messages between variable nodes and check nodes along the edges
- Messages  $\in \{\text{value of var node (NE), erasure (E)}\}$
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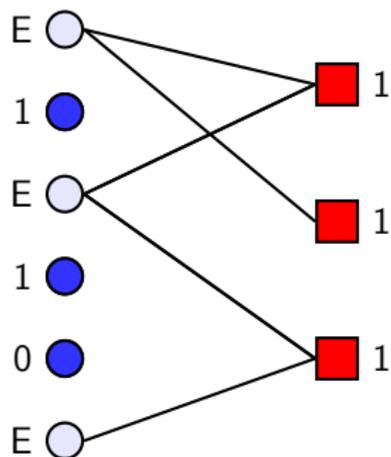
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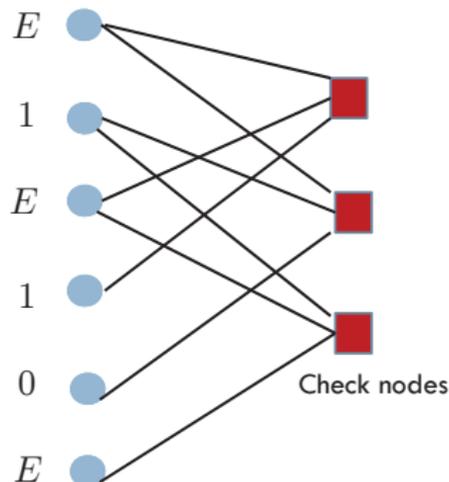
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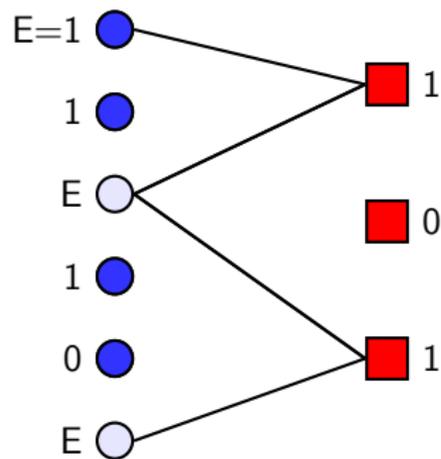
Peeling Step 1



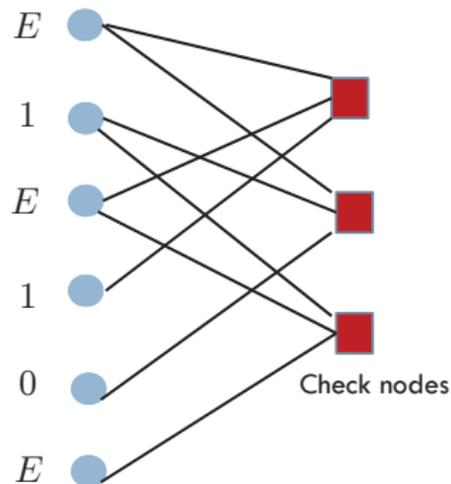
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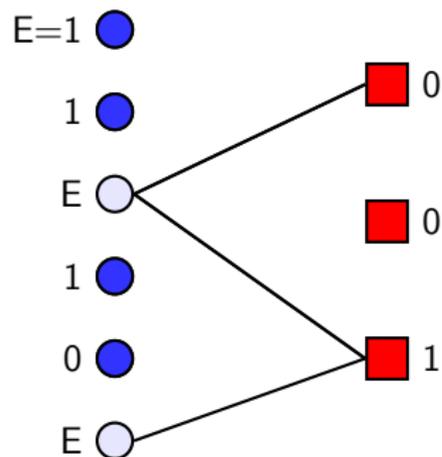
Peeling Step 2



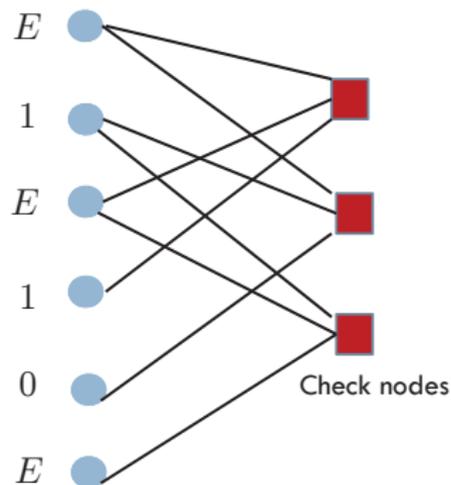
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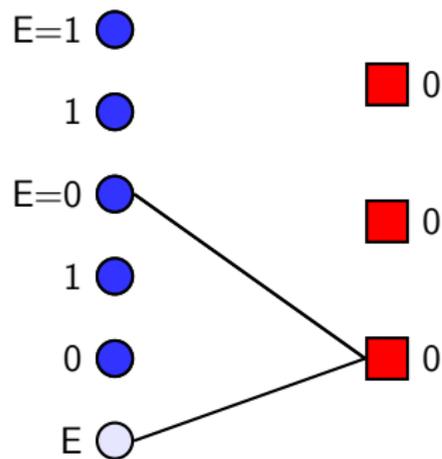
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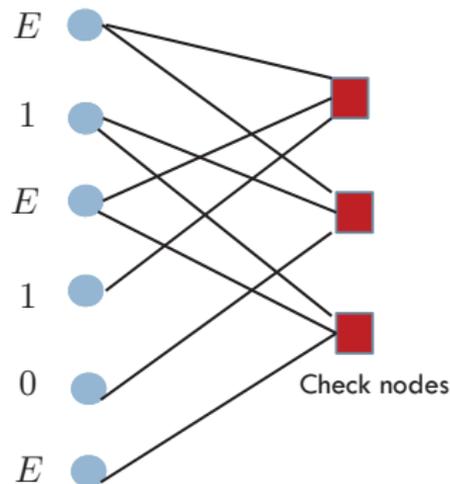
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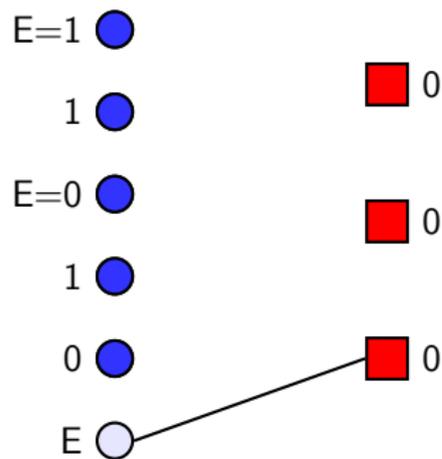
Peeling Step 3



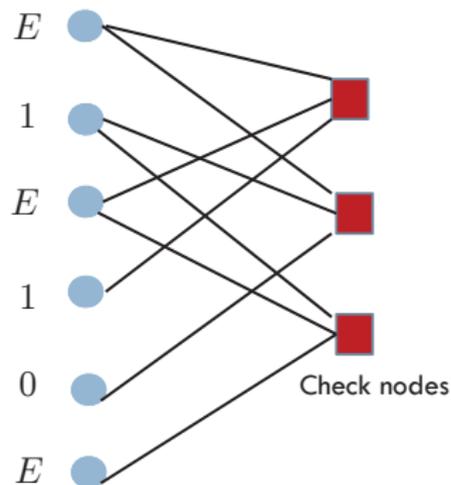
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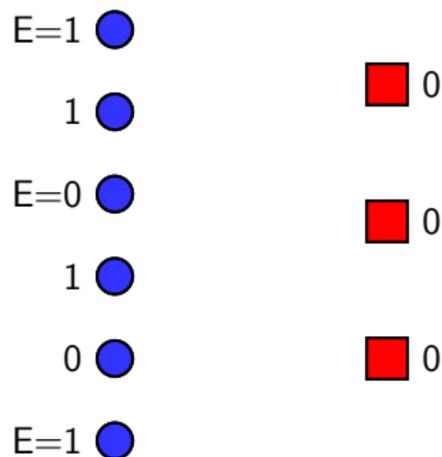
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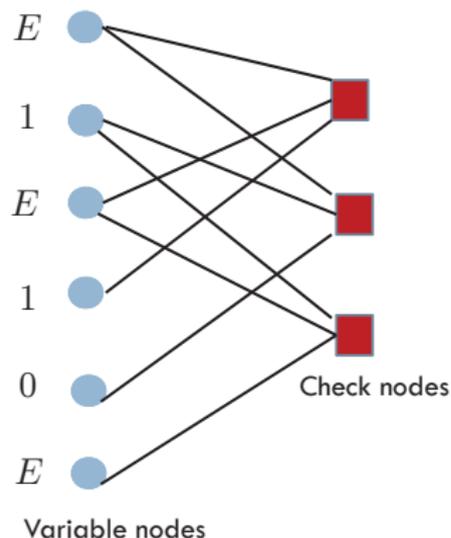
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# Message passing decoder for the BEC



Peeling Step 4



- Pass messages between variable nodes and check nodes along the edges
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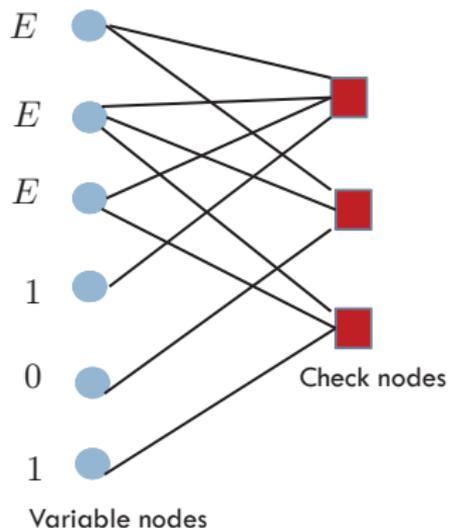
## Peeling decoder is a greedy decoder

$$\mathbf{H} = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$x_1 \oplus x_2 \oplus x_3 \oplus x_4 = 0$$

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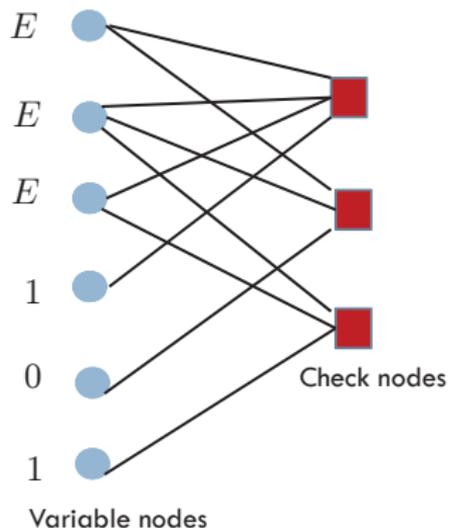
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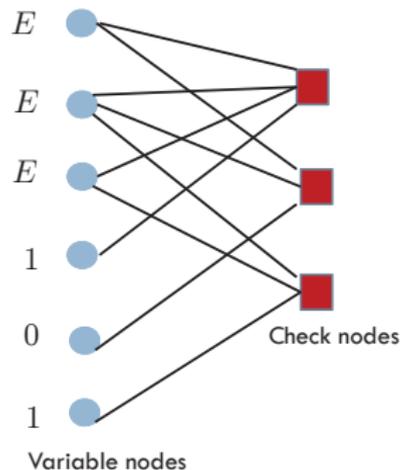
Linearly independent set of equations

$$x_1 \oplus x_1 \oplus x_3 = x_4$$

$$x_1 \oplus x_2 = x_5$$

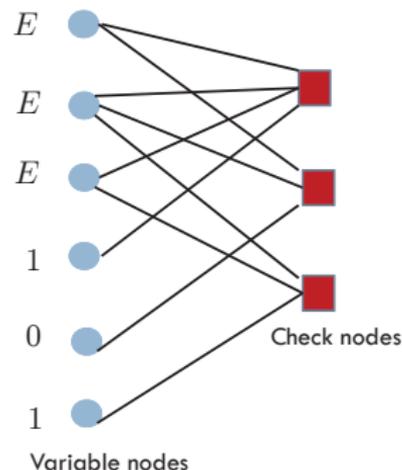
$$x_2 \oplus x_3 = x_6$$

# Degree distributions



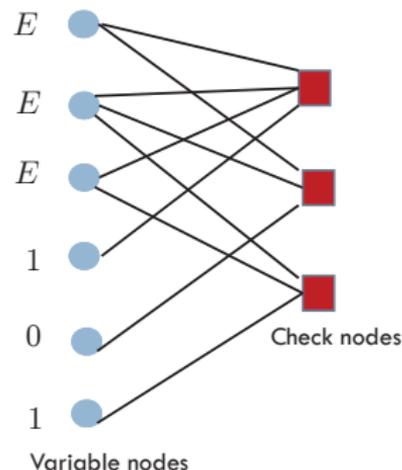
- VN d.d. from node perspective -  $L(x) = \sum_i L_i x^i = \frac{3}{6}x + \frac{2}{6}x^2 + \frac{1}{6}x^3$

# Degree distributions



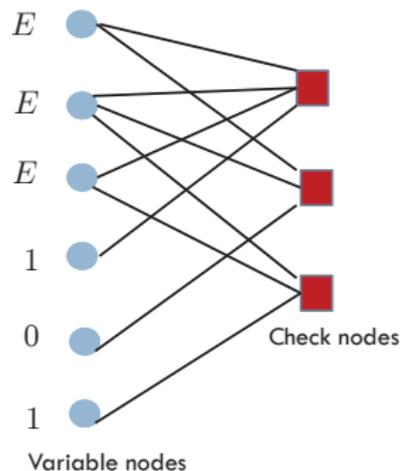
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- VN d.d. from edge perspective -  $\lambda(x) = \sum_i \lambda_i x^{i-1} = \frac{3}{10} + \frac{4}{10}x + \frac{3}{10}x^2$

# Degree distributions



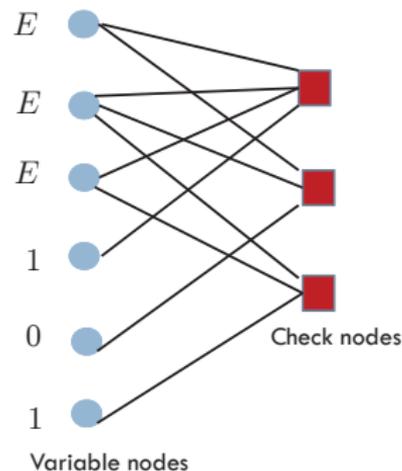
- VN d.d. from node perspective -  $L(x) = \sum_i L_i x^i = \frac{3}{6}x + \frac{2}{6}x^2 + \frac{1}{6}x^3$
- VN d.d. from edge perspective -  $\lambda(x) = \sum_i \lambda_i x^{i-1} = \frac{3}{10} + \frac{4}{10}x + \frac{3}{10}x^2$
- CN d.d. from node perspective -  $R(x) = \sum_i R_i x^i = \frac{2}{3}x^3 + \frac{1}{3}x^4$

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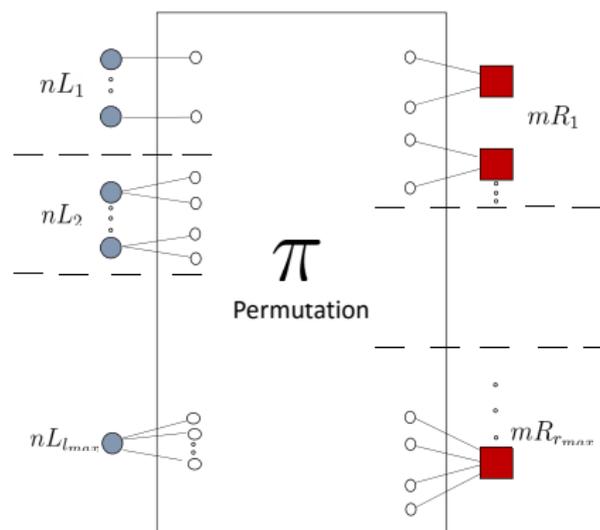
# Degree distributions



- Rate -  $r(\lambda, \rho) = 1 - \frac{l_{\text{avg}}}{r_{\text{avg}}} = 1 - \frac{\int_0^1 \rho(x) dx}{\int_0^1 \lambda(x) dx}$

- VN d.d. from node perspective -  $L(x) = \sum_i L_i x^i = \frac{3}{6}x + \frac{2}{6}x^2 + \frac{1}{6}x^3$
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# LDPC code ensemble



## LDPC( $n, \lambda, \rho$ ) ensemble

- Ensemble of codes obtained by using different permutations  $\pi$
- Assume there is only one edge between every var node and check node
- For every  $n$ , we get an ensemble of codes with the same  $(\lambda, \rho)$
- **Low density parity check** (LDPC) ensemble if graph is of low density

## Analysis of the message passing decoder

- If we pick a code uniformly at random from the LDPC( $n, \lambda, \rho$ ) ensemble and use it over a BEC( $\epsilon$ ) with  $l$  iterations of message passing decoding, what will be the probability of erasure  $P_e^n$  in the limit  $l, n \rightarrow \infty$  ?

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  - For almost all realizations  $P_e^n$  concentrates around the average

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## Relevant literature

- Papers by Luby, Mitzenmacher, Shokrollahi, Spielman, Stemann 97-'02
- Explained in Modern coding theory by Richardson and Urbanke
- Henry Pfister's course notes on his webpage

## Analysis of the message passing decoder

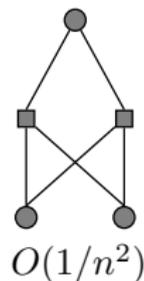
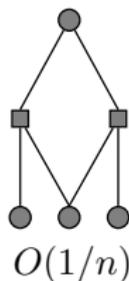
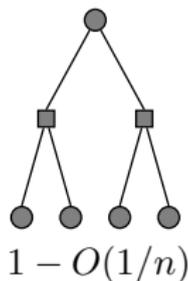
### Computation graph

Computation graph  $\mathcal{C}_l(x_1, \lambda, \rho)$  of bit  $x_1$  of depth  $l$  ( $l$ -iterations) is the neighborhood graph of node  $x_1$  of radius  $l$ .

# Analysis of the message passing decoder

## Computation graph

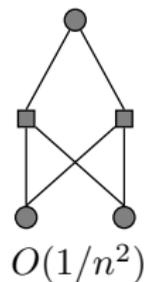
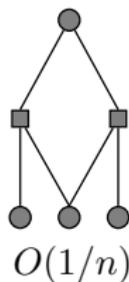
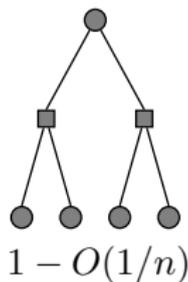
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Computation graph  $\mathcal{C}_l(x_1, \lambda, \rho)$  of bit  $x_1$  of depth  $l$  ( $l$ -iterations) is the neighborhood graph of node  $x_1$  of radius  $l$ . Consider the example  $\mathcal{C}_{l=1}(\lambda(x) = x, \rho(x) = x^2)$



## Computation tree

For fixed  $(l_{max}, r_{max})$ , in the limit of large block lengths a computation graph of depth- $l$  looks like a tree with high probability

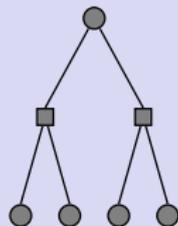
# Analysis of the message passing decoder

## Computation Tree Ensemble- $\mathcal{T}_l(\lambda, \rho)$

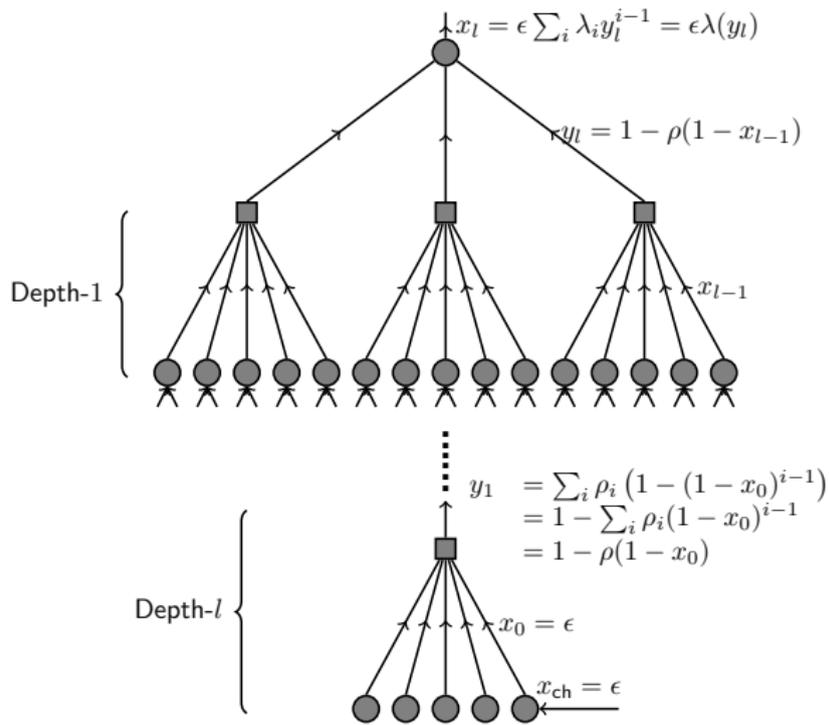
Ensemble of bipartite trees of depth  $l$  rooted in a variable node (VN) where

- Root node has  $i$  children(CN's) with probability  $L_i$
- Each VN has  $i$  children(CN's) with probability  $\lambda_i$
- Each CN has  $i$  children(VN's) with probability  $\rho_i$

Example:  $\mathcal{C}_{l=1}(\lambda(x) = x, \rho(x) = x^2)$



# Density evolution



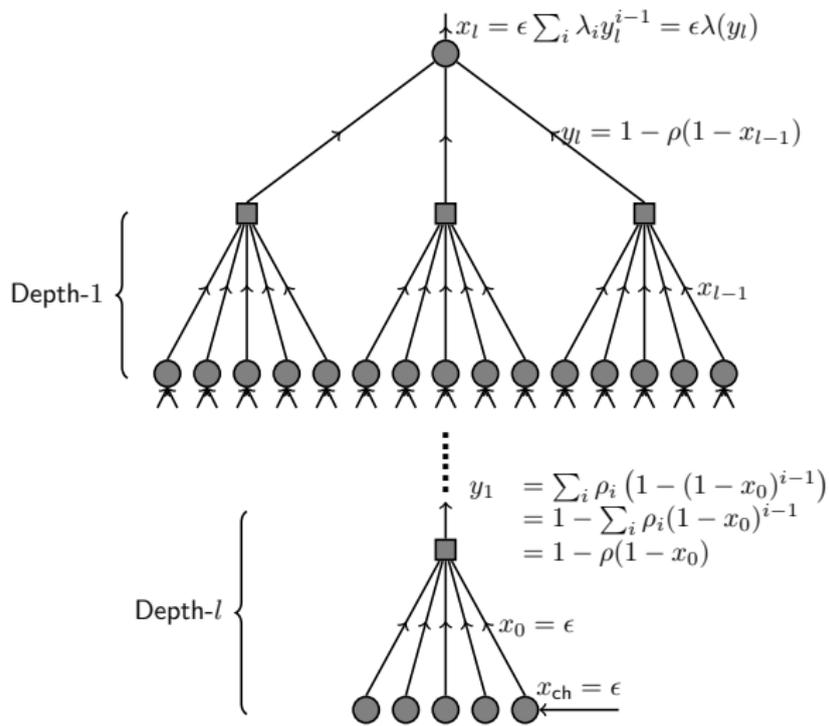
## Recall

- $\rho(x) = \sum_i \rho_i x^{i-1}$
- $\sum_i \rho_i = 1$
- $\lambda(x) = \sum_i \lambda_i x^{i-1}$
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## Recursion

$$x_0 = \epsilon$$

# Density evolution



## Recall

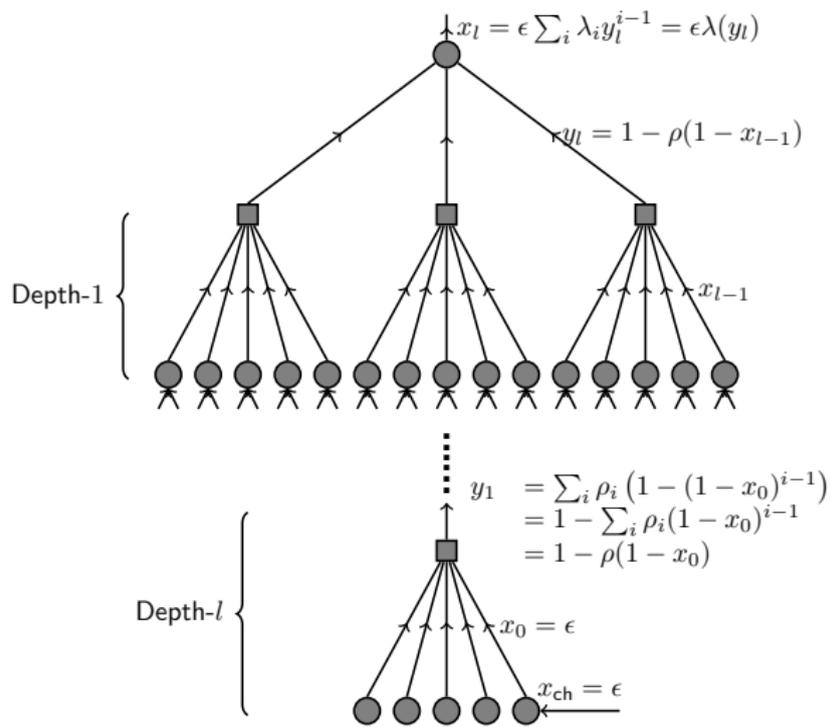
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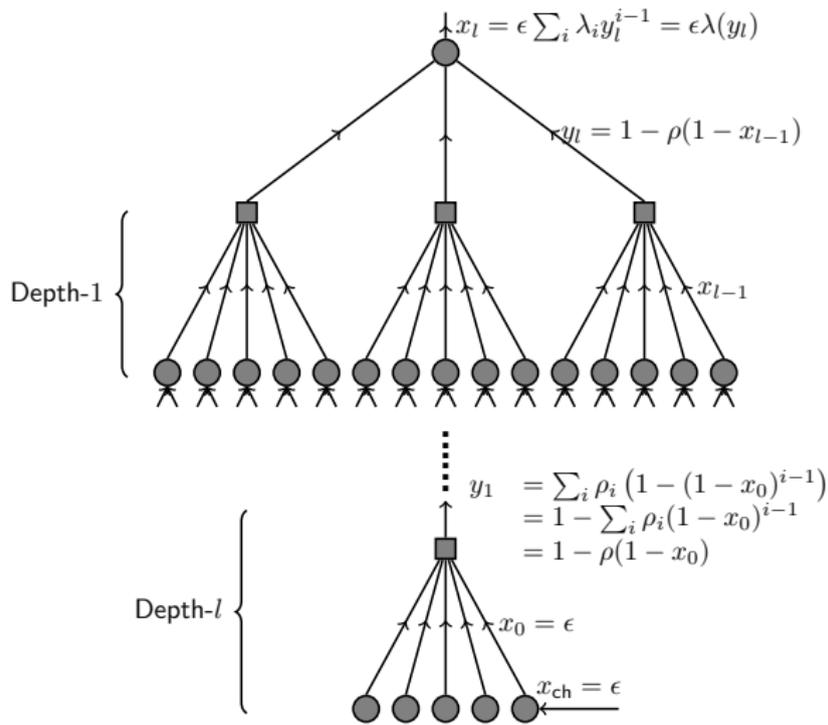
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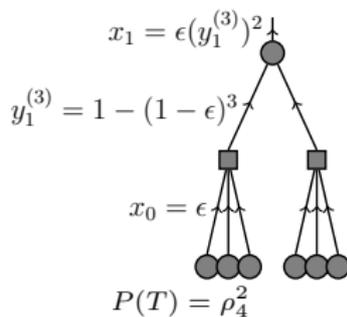
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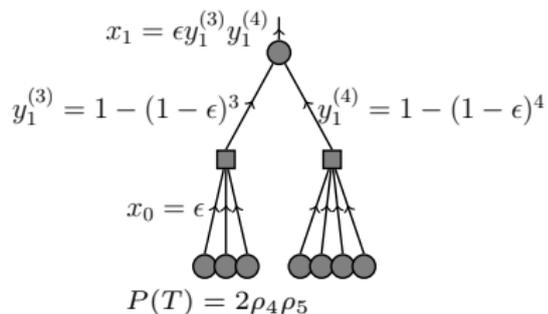
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$$\lambda(x) = x^2, \rho(x) = \rho_4 x^3 + \rho_5 x^4$$



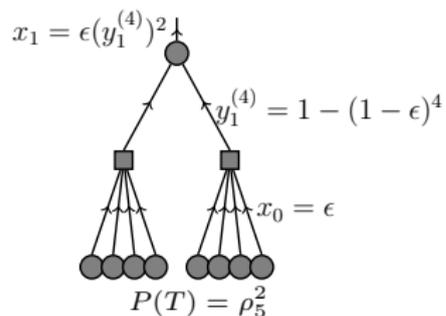
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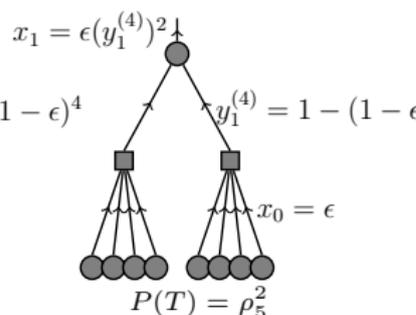
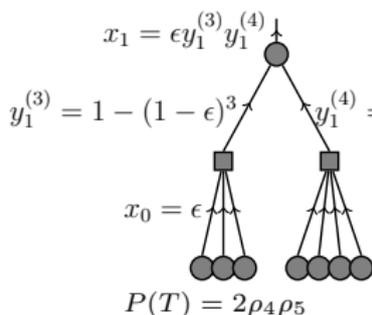
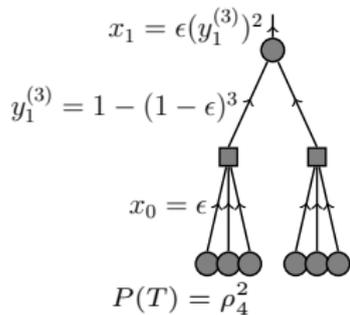
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$$\begin{aligned} \mathbb{E}_{\text{LDPC}(\lambda, \rho)}[x_1] &= \sum_{T \in \mathcal{T}_1(\lambda, \rho)} P(T) * x_1(T, \epsilon) \\ &= \epsilon(\rho_4 y_1^{(3)} + \rho_5 y_1^{(4)})^2 \\ &= \epsilon(1 - \rho_4(1 - \epsilon)^3 - \rho_5(1 - \epsilon)^4)^2 \\ &= \epsilon\lambda(1 - \rho(1 - \epsilon)) \end{aligned}$$

# Threshold

## Convergence condition

$$x_l = \epsilon\lambda(1 - \rho(1 - x_{l-1})) = f(\epsilon, x_{l-1})$$

$x_l$  converges to 0 if  $f(\epsilon, x) < x$ ,  $x \in (0, \epsilon]$

There is a fixed point if  $f(\epsilon, x) = x$ , for some  $x \in (0, \epsilon]$

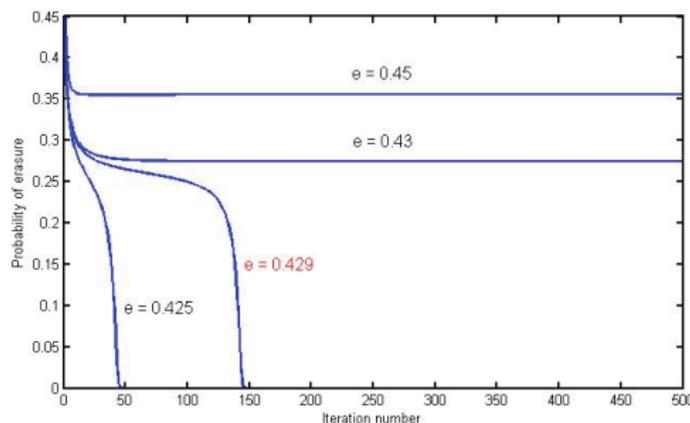
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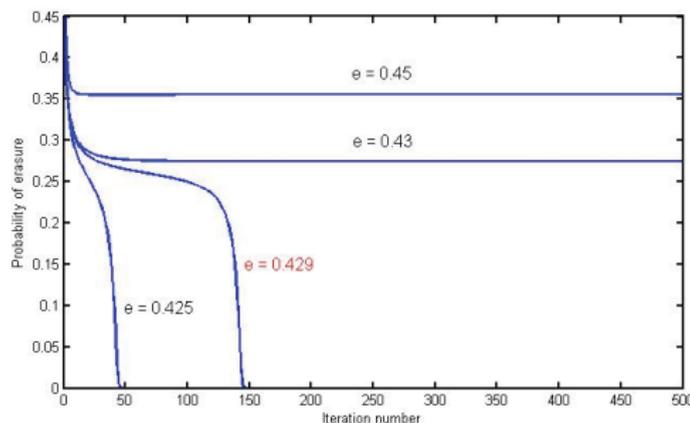
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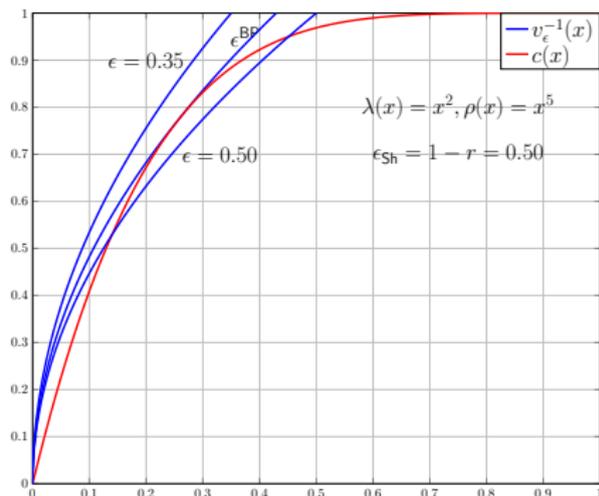
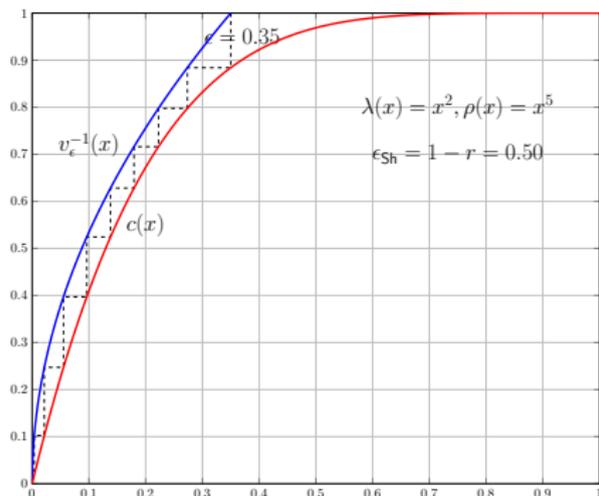
The threshold  $\epsilon^{\text{BP}}(\lambda, \rho)$  is defined as

$$\epsilon^{\text{BP}}(\lambda, \rho) = \sup\{\epsilon \in [0, 1] : x_l \rightarrow 0 \text{ as } l \rightarrow \infty\}$$

# Exit charts - Ashikmin, Kramer, ten Brink'04

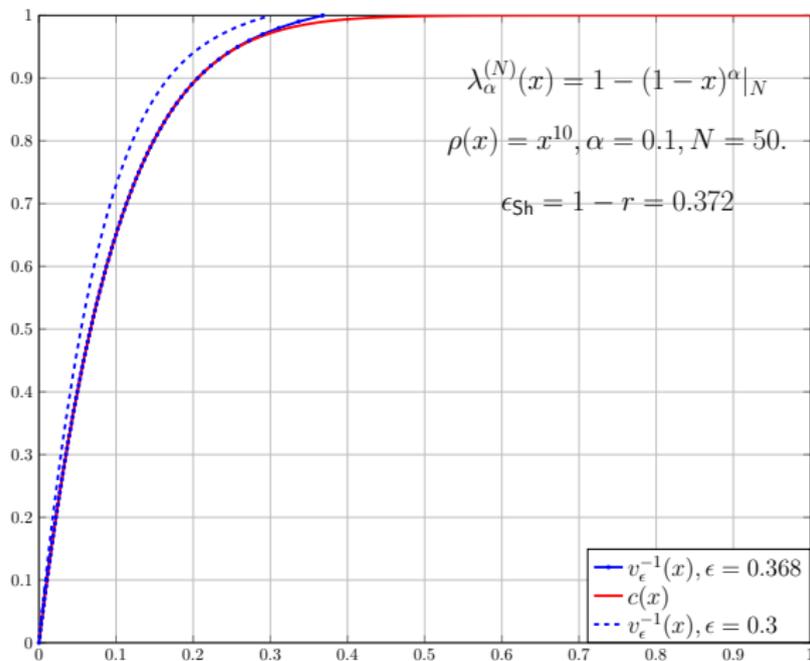
## Node functions

- Var node function:  $v_\epsilon(x) = \epsilon\lambda(x)$
- Check node function:  $c(x) = 1 - \rho(1 - x)$



# Optimality of EXIT chart matching

- Var node function:  $v_\epsilon(x) = \epsilon\lambda(x)$
- Check node function:  $c(x) = 1 - \rho(1 - x)$



# Summary

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- Can you compute the threshold?

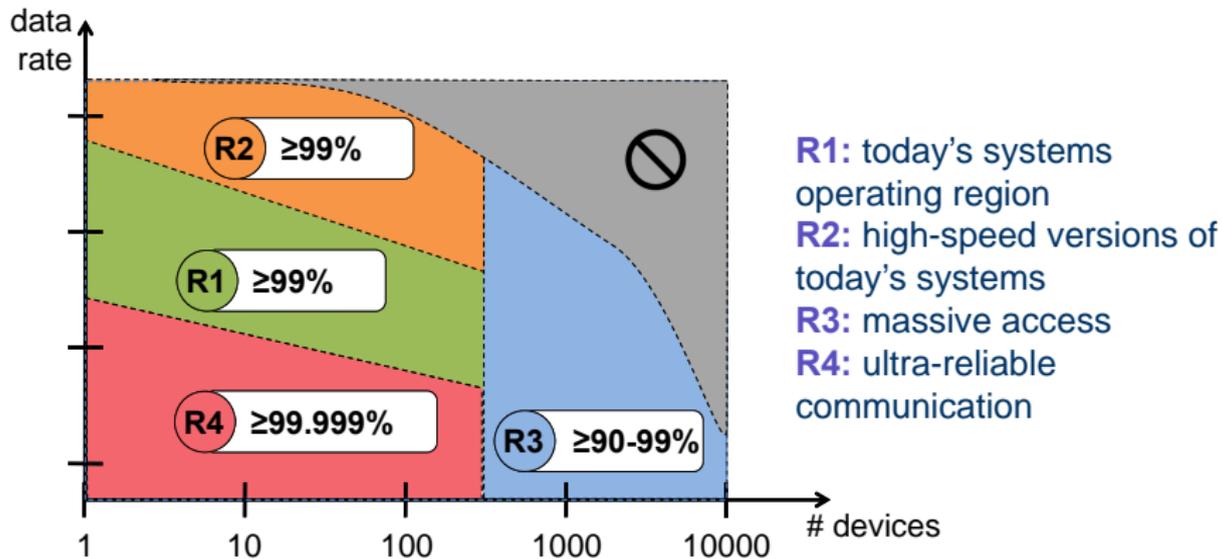
# Summary

- Understand what degree distributions  $(\lambda(x), \rho(x))$  mean
- Given a  $(\lambda, \rho)$  and  $\epsilon$ , what will be the  $P_e^n$  as  $l, n \rightarrow \infty$  ?
- Can you compute the threshold?
- Is a  $(\lambda(x), \rho(x))$  pair optimal?

# Application 1

# The changing mobile landscape

- 5G will not only be “4G but faster” but will support new models such as IoT
- Current wireless - a few devices with sustained connectivity
- Future wireless - **massive** no. of devices requesting **sporadic** connectivity



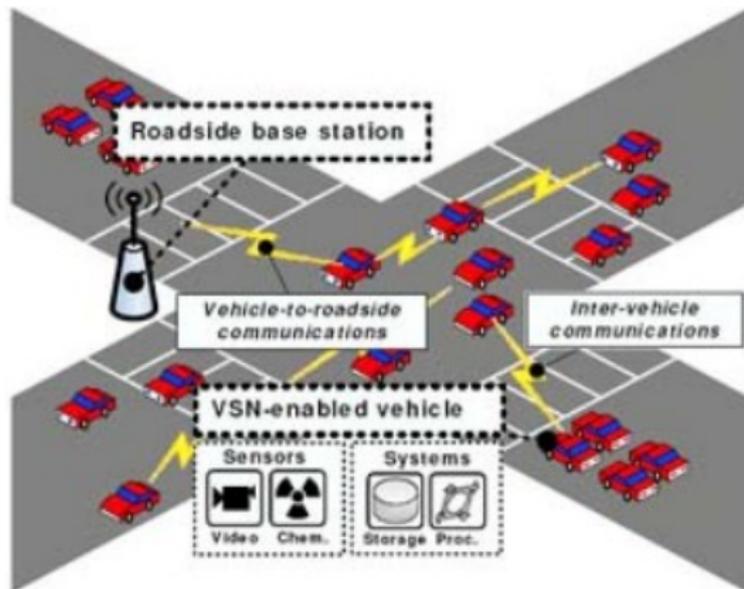
# The changing mobile landscape

- Current wireless - a few devices with sustained connectivity
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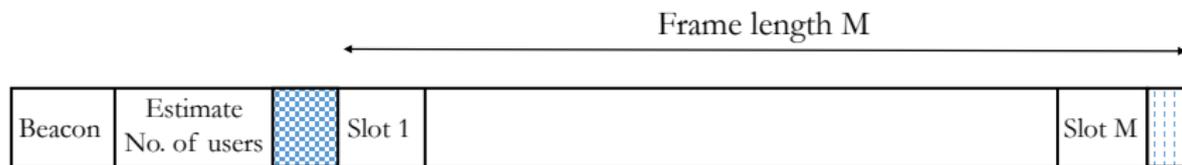
# The changing mobile landscape

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## A possible MAC frame structure

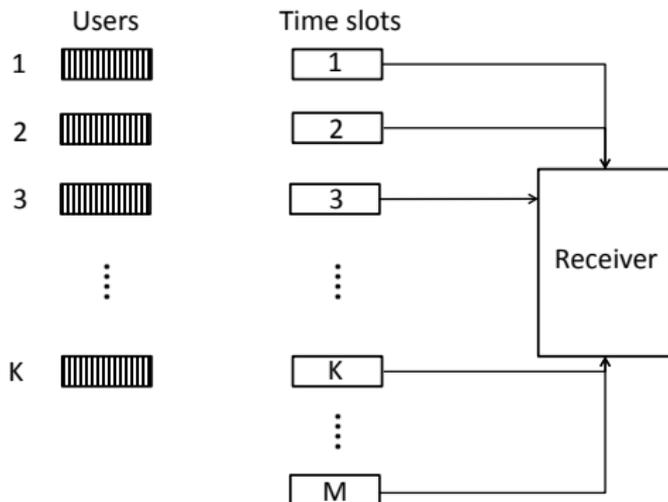
- Total of  $Q$  users out of which  $K$  are active
- $Q$  is very large and  $K$  is a small fraction of  $Q$



- Beacon is used to obtain coarse synchronization
- Each user transmits a signature sequence
- BS estimates the no. of users ( $K$ ) (Chen, Guo '14, Calderbank)
- Picks an  $M$  and broadcasts it

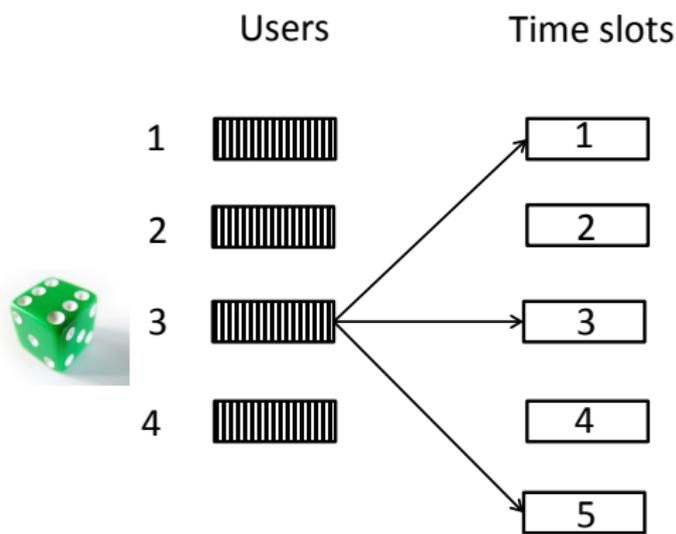
# System under consideration

- Wireless network with  $K$  distributed users (no coordination)
- Each user has one packet of info to transmit to a central receiver
- Total time is split into  $M$  slots (packet duration)
  - Some policy used to decide if they transmit in  $j$ -th slot or not
  - Receiver knows the set of users transmitting in the  $j$ -th slot



# Random access paradigm

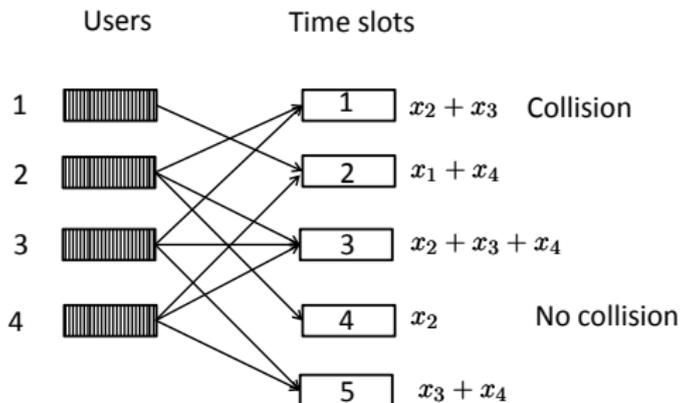
- $k$ -th user:
  - Generates a random variable  $D_k \in \{1, \dots, M\}$
  - Generating PMF is  $f_D$ , i.e.,  $Pr(D_k = i) = f_D[i]$
  - Transmits during  $D_k$  time slots drawn uniformly from  $\{1, \dots, M\}$



- In this example,  $D_3 = 3$  and user 3 transmits in slots  $\{1, 3, 5\}$

# Iterative interference cancellation

- If exactly one user transmits per slot, then packet is decoded w.h.p.
- If more than one user transmits per slot, then collision
  - Rx subtracts previously decoded packets from collided packets
  - If Rx can subtract all but one, remaining packet is decoded w.h.p.
  - Otherwise, the received packet is saved for future processing
  - Once all  $K$  packets recovered, an ACK terminates the transmission
  - Similar to interference cancellation in multi-user detection



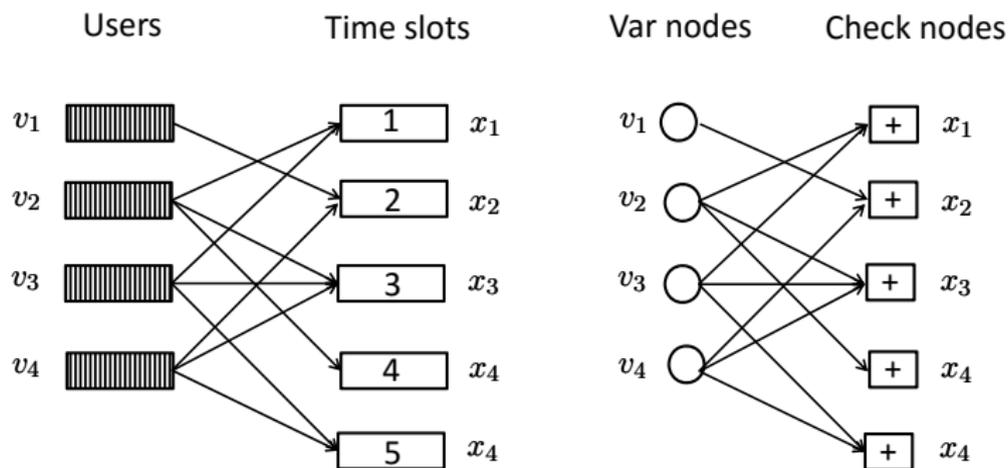
## Performance measure - Efficiency

- Suppose  $M$  time slots needed to successfully transmit all  $K$  packets
- Then, the efficiency of the system is said to be

$$\eta = K/M \text{ packets/slot}$$

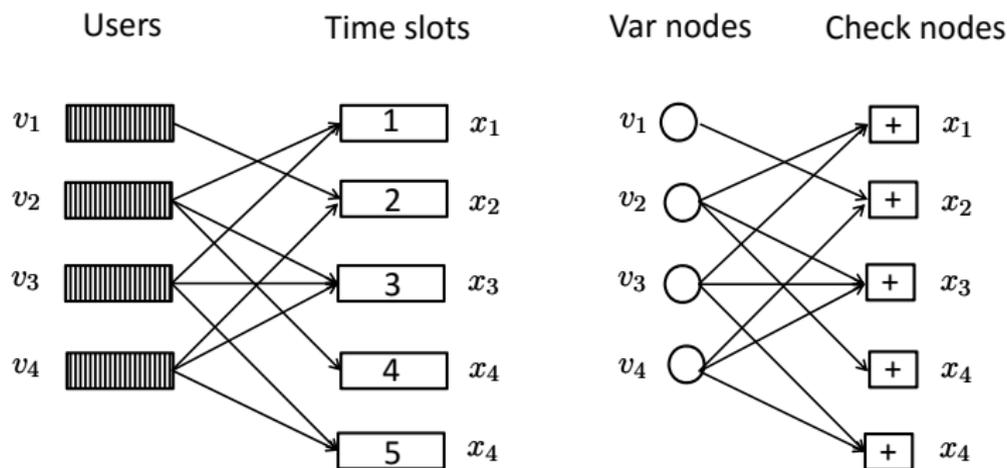
## Graphical representation (Liva 2012)

- Tanner graph representation for the transmission scheme
- Variable nodes  $\leftrightarrow$  users, Check nodes  $\leftrightarrow$  received packets
- Message-passing decoder - [peeling decoder](#) for the erasure channel



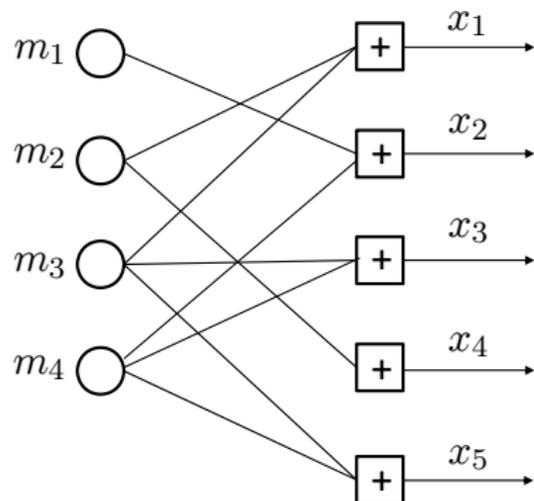
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- $L_i$  ( $R_i$ ) - fraction of left (right) nodes with degree  $i$  - notice that  $L_i = f_D[i]$
- $\lambda_i$  ( $\rho_i$ ) - fraction of edges connected to left (right) nodes with deg  $i$

## Low density generator matrix (LDGM) codes



- $L(x) = \frac{1}{4}x + \frac{1}{4}x^2 + \frac{1}{2}x^3$
- $\lambda(x) = \frac{1}{9} + \frac{2}{9}x + \frac{6}{9}x^2$
- $R(x) = \frac{1}{5}x + \frac{4}{5}x^2$
- $\rho(x) = \frac{1}{9} + \frac{8}{9}x$
- Rate  $R = \frac{\int_0^1 \lambda(x) dx}{\int_0^1 \rho(x) dx}$

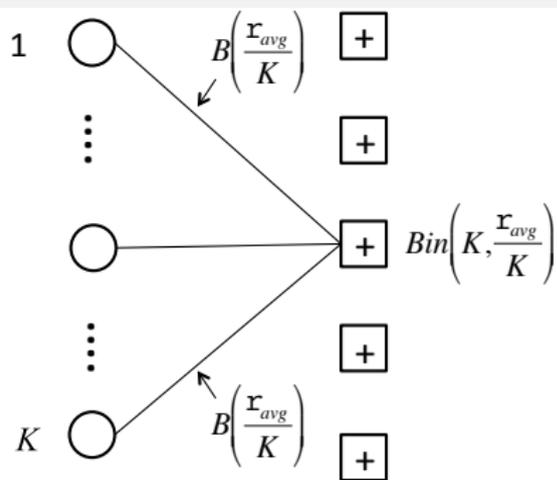
### DE for LDPC

$$\begin{aligned}x_0 &= \epsilon \\y_l &= 1 - \rho(1 - x_{l-1}) \\x_l &= \epsilon \lambda(y_l) \\x_l &= \epsilon \lambda(1 - \rho(1 - x_{l-1}))\end{aligned}$$

### DE for LDGM

$$\begin{aligned}x_0 &= 1 \\y_l &= 1 - \rho(1 - x_{l-1}) \\x_l &= \lambda(y_l) \\x_l &= \lambda(1 - \rho(1 - x_{l-1}))\end{aligned}$$

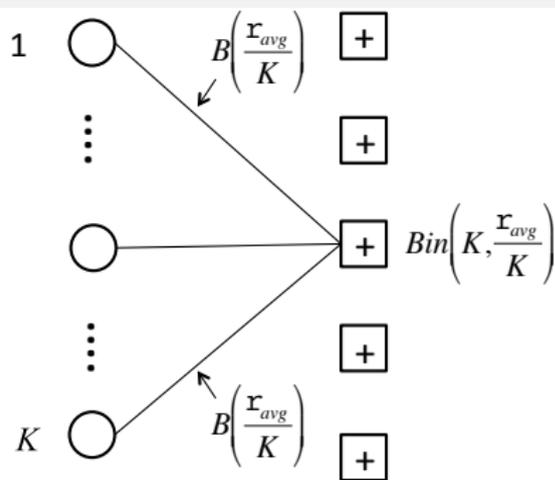
## Poisson approximation for check node d.d.



Slot transmission probability

User  $k$  transmits in slot  $m$  with prob.  $p = \sum_{i=1}^{\infty} L_i \frac{i}{M} = \frac{l_{avg}}{M} = \frac{r_{avg}}{K}$

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Optimal multiple access policy

- Poisson approximation for  $R(x)$  as  $K, M \rightarrow \infty$
- Finding optimal  $f_D$  - same as finding optimal  $\lambda(x)$  for  $\rho(x) = e^{-r_{avg}(1-x)}$

## Intuition behind the main result (Narayanan,Pfister'12)

Convergence condition :  $\rho(1 - \lambda(y)) > 1 - y$

$$\rho(1 - \lambda(y)) = 1 - y$$

$$e^{-\mathbf{r}_{avg}\lambda(y)} = e^{\ln(1-y)}$$

$$\Rightarrow -\mathbf{r}_{avg}\lambda(y) = \ln(1 - y) = -\sum_{i=1}^{\infty} \frac{y^i}{i}$$

$$\Rightarrow \mathbf{r}_{avg} \sum_i \lambda_i y^i = \sum_{i=1}^{\infty} \frac{y^i}{i}$$

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$$\rho(1 - \lambda(y)) = 1 - y$$

$$e^{-r_{avg}\lambda(y)} = e^{\ln(1-y)}$$

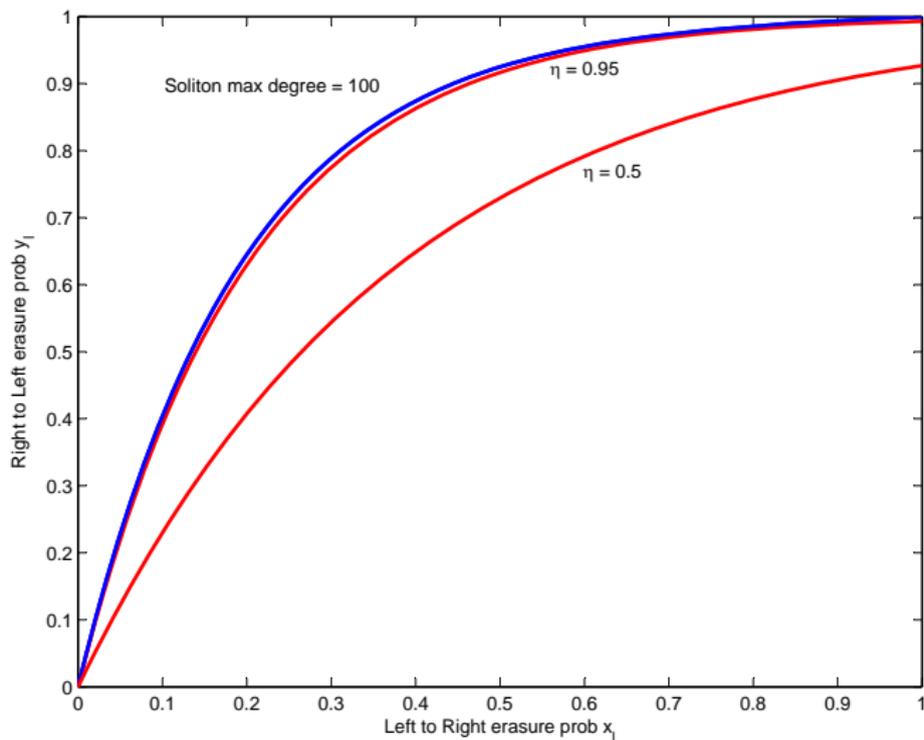
$$\Rightarrow -r_{avg}\lambda(y) = \ln(1 - y) = -\sum_{i=1}^{\infty} \frac{y^i}{i}$$

$$\Rightarrow r_{avg} \sum_i \lambda_i y^i = \sum_{i=1}^{\infty} \frac{y^i}{i}$$

$$r_{avg}\lambda_i = \frac{1}{i}$$

$$\sum_i \lambda_i = 1 \Rightarrow \boxed{r_{avg} = \sum_i \frac{1}{i}, \lambda_i = \frac{1/i}{\sum_i 1/i}} \Rightarrow \boxed{L_i = \frac{1}{i(i-1)}, i \geq 2}$$

# Graphical interpretation - EXIT chart



## Main result

- For coordinated transmission, clearly  $\eta = 1$ ,

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- For coordinated transmission, clearly  $\eta = 1$ ,
- ALOHA provides  $\eta \approx 0.37$
- But, even for uncoordinated transmission,  $\eta \rightarrow 1$  as  $K \rightarrow \infty$

Optimal distribution is soliton:  $f_D[i] = \frac{1}{i(i-1)}$

No. of times	1	2	3	4	...	$M$
Fraction of users	$\frac{1}{M}$	$\frac{1}{2}$	$\frac{1}{6}$	$\frac{1}{12}$	...	$\frac{1}{M(M-1)}$

# Balls in bins

- $M$  balls thrown into  $N$  bins uniformly at random
- If every bin has to be non-empty with prob  $1 - \delta$ , how large should  $M$  be ?

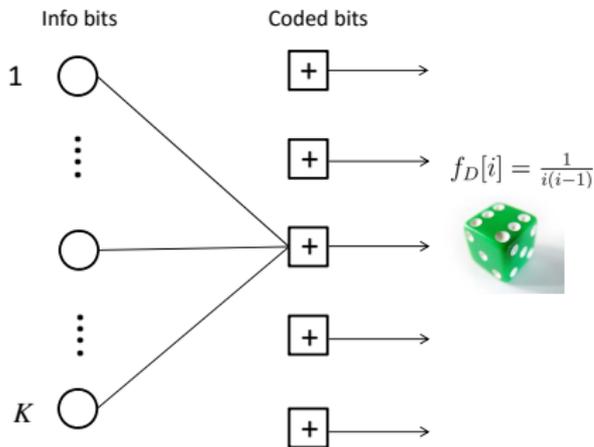
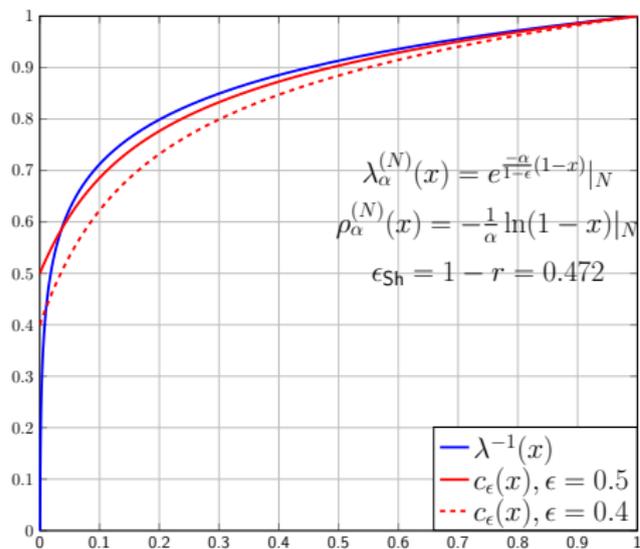
## Balls in bins

- $M$  balls thrown into  $N$  bins uniformly at random
- If every bin has to be non-empty with prob  $1 - \delta$ , how large should  $M$  be ?

$$N \log \frac{N}{\delta}$$

- For the multiple access problem, an empty bin means a wasted time slot
- Note that for the soliton the average number of edges is indeed  $N \log N$ )

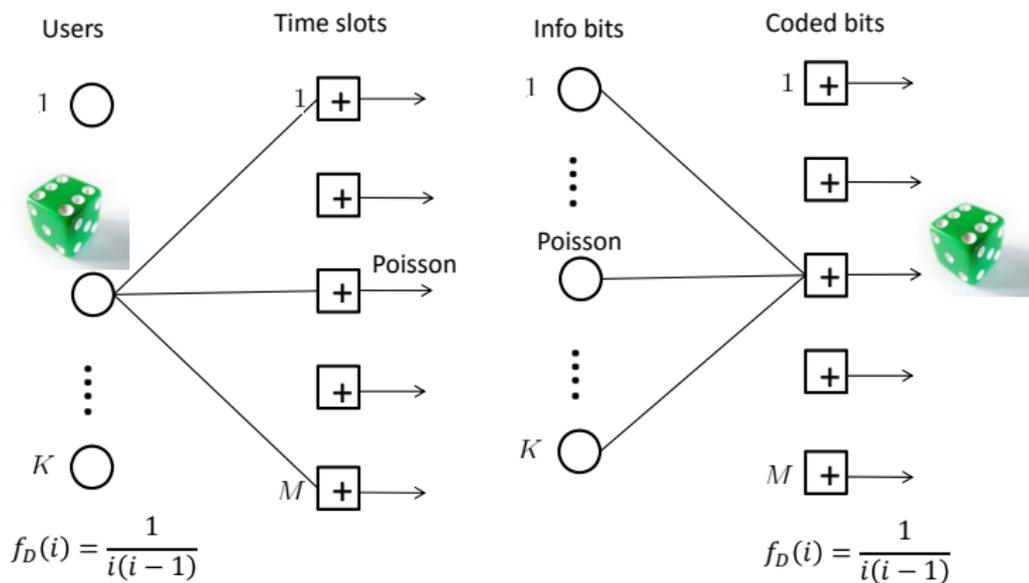
# Poisson, soliton pair is optimal for rateless codes



- $x = \lambda(1 - (1 - \epsilon)\rho(1 - x))$
- $\lambda(x) = e^{-\frac{\alpha}{1-\epsilon}(1-x)}$ , optimal right degree is soliton:  $\rho(x) = -\frac{1}{\alpha} \ln(1 - x)$

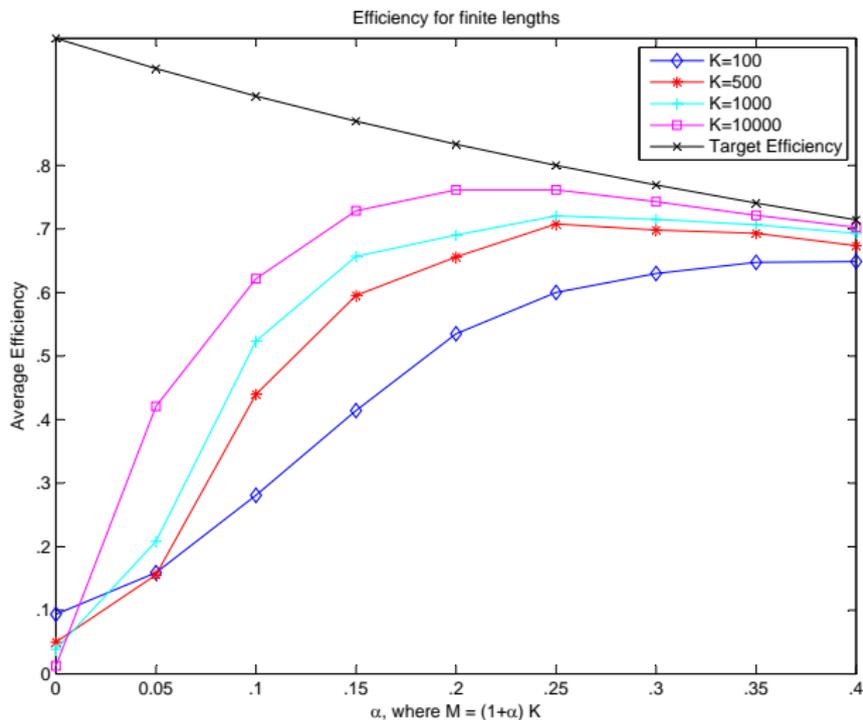
Degree of nodes	1	2	3	4	...	$i$	...	$K$
Fraction: $f_D[i]$	$\frac{1}{K}$	$\frac{1}{2}$	$\frac{1}{6}$	$\frac{1}{12}$	...	$\frac{1}{i(i-1)}$	...	$\frac{1}{K(K-1)}$

# Connection with Luby Transform (LT) codes



- For rateless codes  $\lambda(x)$  is Poisson and  $\rho(x)$  is soliton
- For multiple access  $\rho(x)$  is Poisson, **optimal  $\lambda(x)$  is soliton**
- Our result shows that both are optimal pairs

# Simulation Results



- Even for  $K = 10000$ , efficiency close to 0.8 can be obtained

## Some open problems

- Fundamental limits on universal multiple access, i.e.  $K$ ,  $\epsilon$  not known
- Uncoordinated multiple access with power constraint and Gaussian noise
  - Power penalty for repeating information  $\log n$  times on the average
  - Can we achieve the equal rate point on the MAC region with simple decoding?

## Back to theory: from erasures to errors

## Finite field with $p$ elements

$p$  is prime

- $\mathbb{F}_p = \{0, 1, 2, \dots, p-1\}$
- $a \oplus b = (a + b) \bmod p$
- $a \odot b = (ab) \bmod p$
- We can  $+$ ,  $\times$ ,  $\div$ , inverses
- $W$  is a (primitive) element such that  $1, W, W^2, \dots, W^{p-1}$  are distinct

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Example  $\mathbb{F}_5$

- $W = 2$
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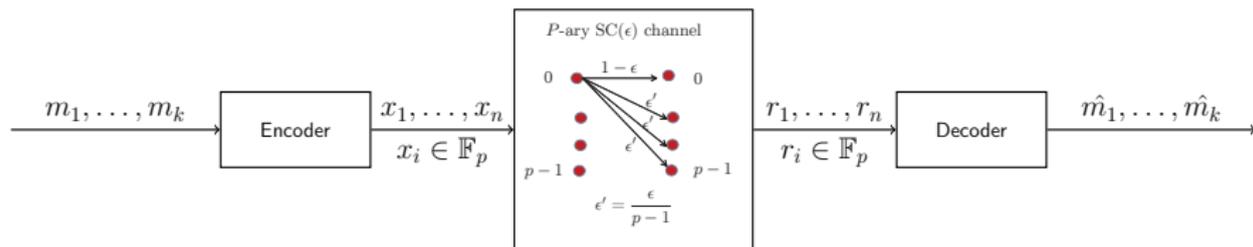
### Example $\mathbb{F}_5$

- $W = 2$
- $W^0 = 1, W^1 = 2, W^2 = 4, W^3 = 3$

### $p$ need not be prime

- Everything can be extended to finite fields with  $q = 2^r$  elements
- May be extended to integers - not sure

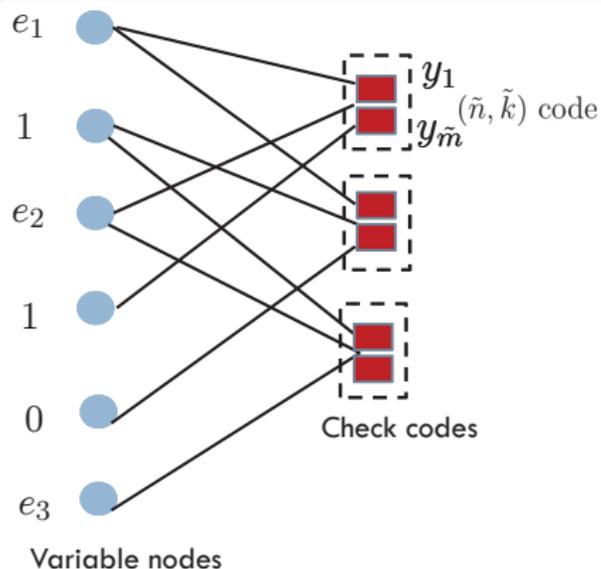
# $p$ -symmetric channel and error correction



## Error correction coding

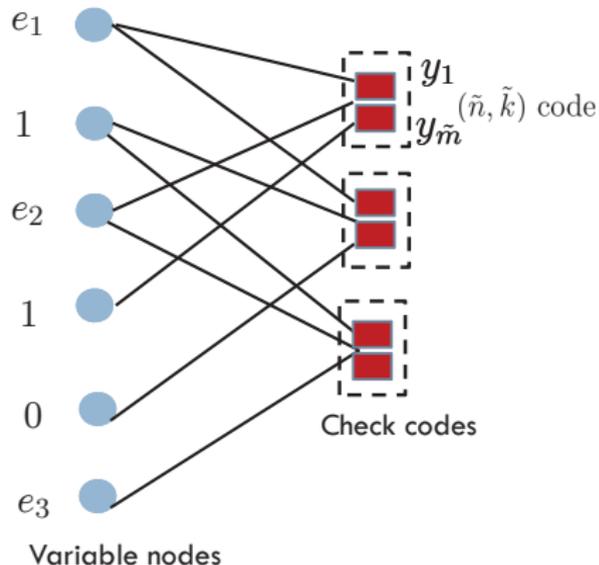
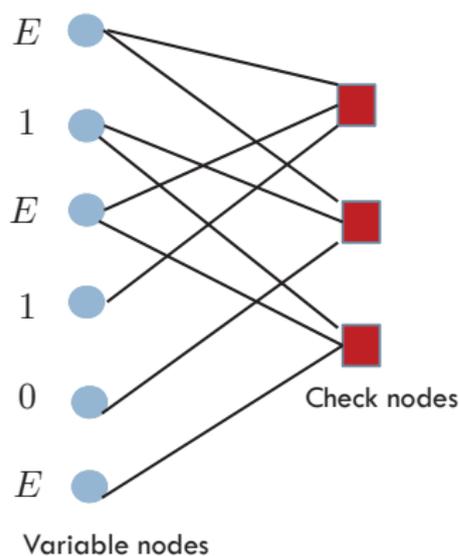
- Another simple channel model which has been extensively considered
- Has been the canonical model for algebraic coding theorists

# Generalized LDPC code and error channels



- GLDPC introduced by Tanner in 1981
- Each check is a  $(\tilde{n}, \tilde{k})$ ,  $t$ -error correcting code
- If there are  $\leq t$  errors in a check, it can be recovered
- For now, assume no miscorrections

## Peeling process is same for erasure and error channels



- Assume 1-error correcting check code and no miscorrections
- One-to-one correspondence between messages passed - DE can be used
- Not optimal for the error channel but it is not bad at high rates
- Spatially coupled versions are optimal at high rates (Jian, Pfister and N)

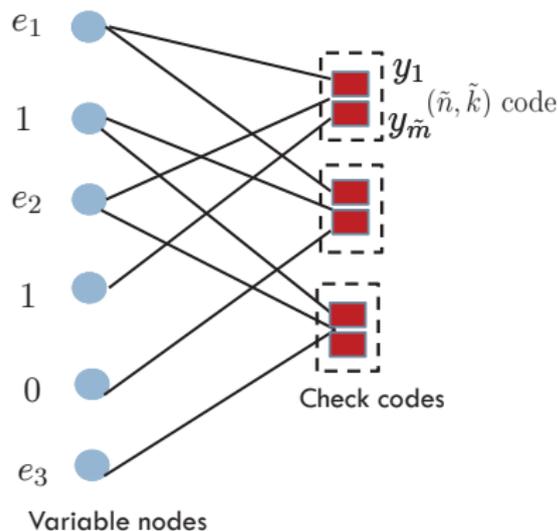
## Erasures to errors - tensoring and peeling

$$H = \begin{bmatrix} 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 \end{bmatrix}$$

 $\otimes$ 

$$B = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & W & W^2 & W^3 & W^4 & W^5 \end{bmatrix}$$

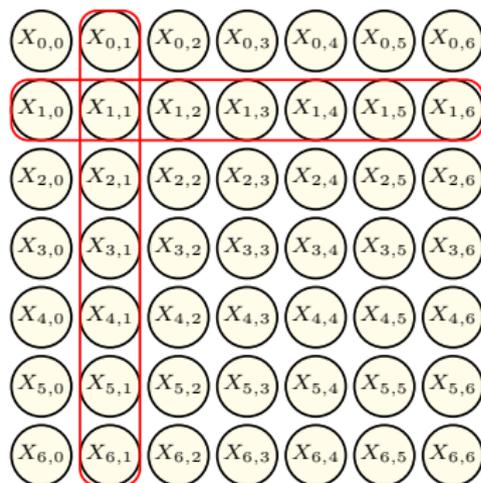
$$\tilde{H} = \begin{bmatrix} 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & W^2 & W^3 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & W & 0 & 0 & W^4 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & W & W^2 & 0 & 0 & W^5 \end{bmatrix}$$



- $W$  is a primitive element in the field
- Each check is a 1-error correcting code
- If there is exactly one error in a check, it can be recovered

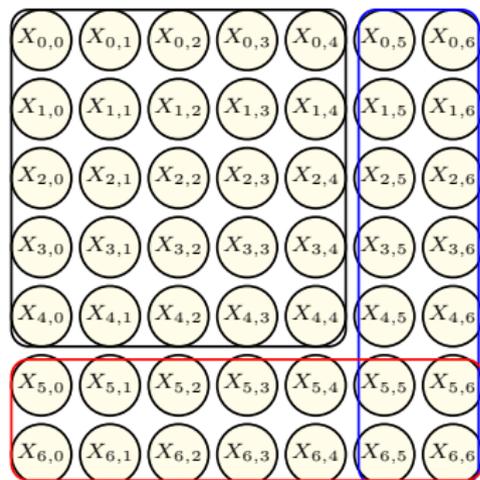
# Product code

- Special case of generalized LDPC code
- Let component code  $\mathcal{C}$  be an  $(\tilde{n}, \tilde{k}, \tilde{d}_{\min})$  linear code
- Well-known that  $\mathcal{P}$  is an  $(\tilde{n}^2, \tilde{k}^2, \tilde{d}_{\min}^2)$  linear code



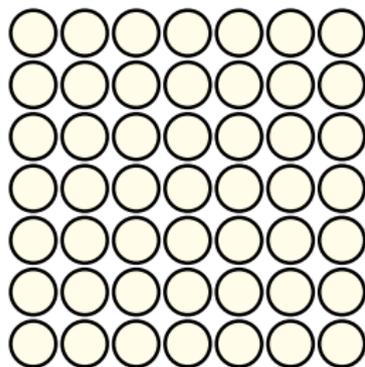
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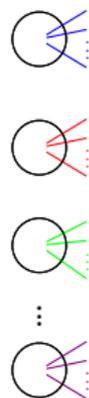


# Peeling decoding of product codes

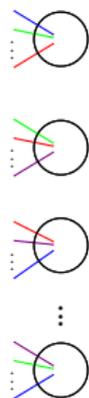
- Hard-decision “cascade decoding” by Abramson in 1968
- Identical to a peeling decoder
- Example:  $t = 2$ -error-correcting codes, bounded distance decoding



row codes

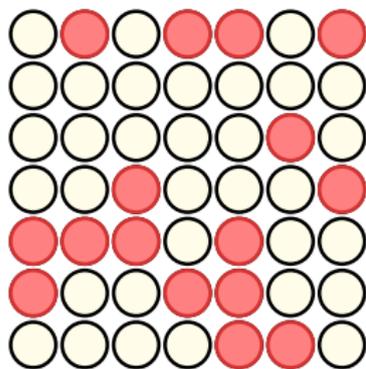


column codes



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Received block

row codes



⋮



column codes

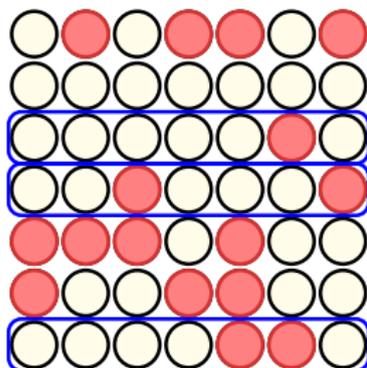


⋮



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Row decoding

row codes



⋮



column codes

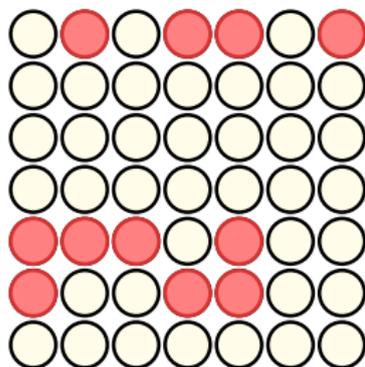


⋮



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Row decoding

row codes



⋮



column codes

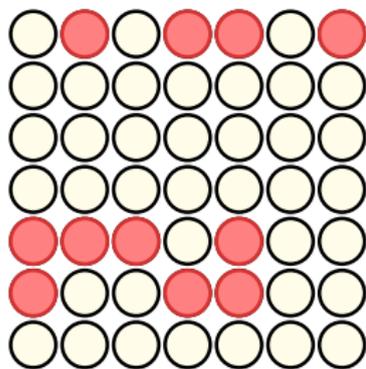


⋮



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Column decoding

row codes



⋮



column codes

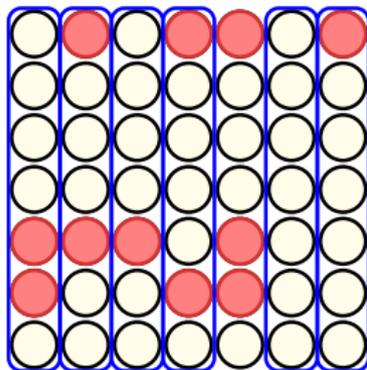


⋮



# Peeling decoding of product codes

- Hard-decision “cascade decoding” by Abramson in 1968
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Column decoding

row codes



⋮



column codes

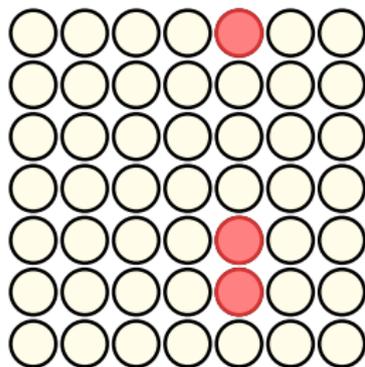


⋮



# Peeling decoding of product codes

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- Example:  $t = 2$ -error-correcting codes, bounded distance decoding



row codes



⋮



column codes

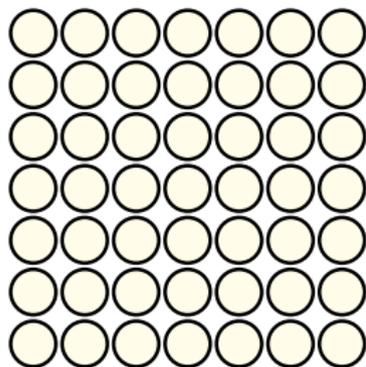


⋮



# Peeling decoding of product codes

- Hard-decision “cascade decoding” by Abramson in 1968
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- Example:  $t = 2$ -error-correcting codes, bounded distance decoding



Decoding successful

row codes



⋮



column codes

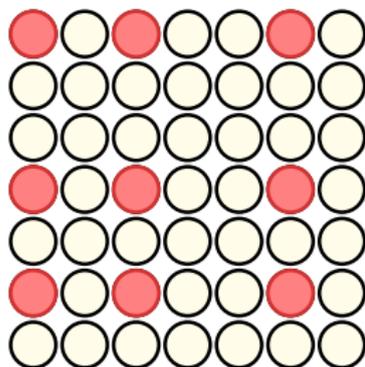


⋮



# Peeling decoding of product codes

- Hard-decision “cascade decoding” by Abramson in 1968
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- Example:  $t = 2$ -error-correcting codes, bounded distance decoding



Or trapped in a **stopping set**

row codes



⋮



column codes



⋮



# Density Evolution(DE) for Product Codes -Justesen et al

What is different about DE?

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## Main Idea

- Removal of **corrected vertices** (degree  $\leq t$ ) from row codes  $\Leftrightarrow$  removal of random edges from column codes uniformly at random
- **#** of errors in row/column changes after each iter
- Track the distribution

row codes



column codes



## DE continued

Tail of the Poisson distribution

$$\pi_t(m) = \sum_{j \geq t} e^{-m} m^j / j!$$

Effect of first step of decoding

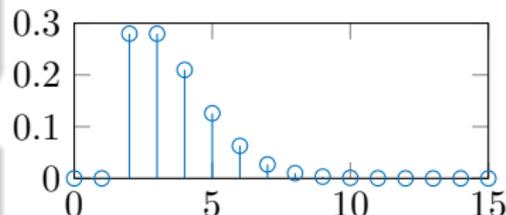
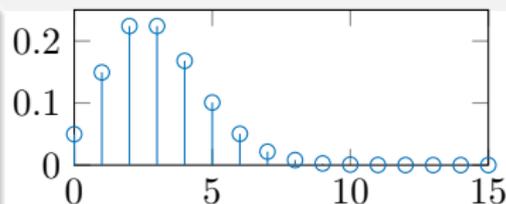
If the # errors is Poisson with mean  $M$ , Mean # of errors after decoding is

$$m(1) = \sum_{j \geq t+1} j e^{-M} M^j / j! = M \pi_t(M)$$

# Evolution of degree distribution ( $d = 2$ ) - first iteration

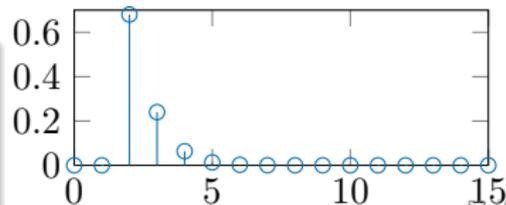
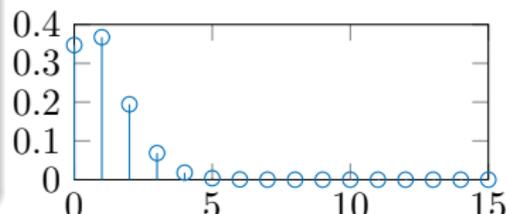
## Row decoding

- Before row decoding
  - **Distribution:** Poisson( $M$ ), **Mean:**  $M$
- After row decoding
  - **Distribution:** Truncated Poisson( $M$ )
  - **Mean:**  $M\pi_t(M) = m(1)$



## Column decoding

- Before column decoding
  - **Distribution:** Poisson( $m(1)$ ), **Mean:**  $m(1)$
- After column decoding
  - **Distribution:** Truncated Poisson( $m(1)$ )
  - **Mean:**  $m(2) = M\pi_t(m(1))$



## After every decoding

- Distribution is a Truncated Poisson( $m(j)$ )
- $P[\#errors = i] = b \frac{m(j)^i}{i!}$

# Evolution of the degree distribution - $j$ th iteration

## Recursion

- $m(0) = M$
- $m(1) = M\pi_t(M)$
- $m(j) = M\pi_t(m(j-1))$

## Reduction in the parameter

- Average no. of errors in each row (column) =  $m(j)\pi_t(m(j))$
- Decoding of rows reduces the parameter by  $\frac{m(j)\pi_t(m(j))}{m(j-1)\pi_t(m(j-1))} = \frac{M\pi(m(j))}{m(j-1)}$
- New parameter is  $m(j+1) = M\pi(m(j))$

## Threshold

In the limit of large  $\tilde{n}$  (length in each dimension), a  $t$ -error correcting product code can correct  $\tilde{n}M$  errors when

$$M < \min_m \left\{ \frac{m}{\pi_t(m)} \right\}$$

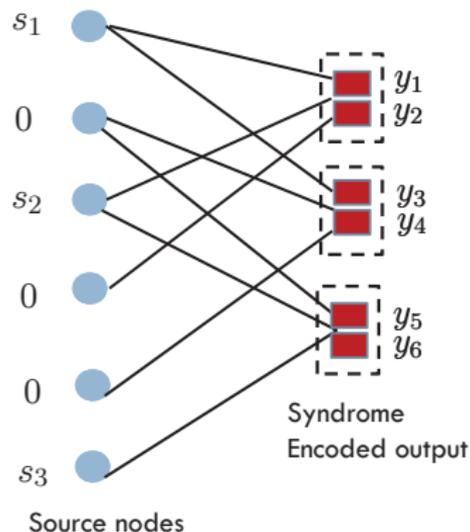
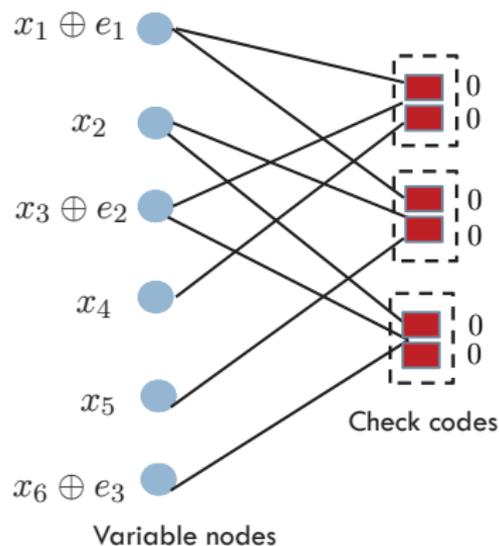
## Thresholds for asymptotically large field size

$$\text{Threshold} = \frac{\# \text{ of parity symbols}}{\# \text{ of errors}}$$

	$d = 2$	$d = 3$	$d = 4$	$d = 5$	$d = 6$	$d = 7$	$d = 8$
$t = 1$	4.0	2.4436	2.5897	2.8499	3.1393	3.4378	3.7383
$t = 2$	2.3874	2.5759	2.9993	3.4549	3.9153	4.3736	4.8278
$t = 3$	2.3304	2.7593	3.3133	3.8817	4.4483	5.0094	5.5641
$t = 4$	2.3532	2.9125	3.5556	4.2043	4.8468	5.4802	6.1033

Notice that  $L, K = O\left(N^{\frac{1-d}{d}}\right)$

# Syndrome source coding



- $H\underline{x} = 0$
- Receive -  $\underline{r} = \underline{x} \oplus \underline{e}$
- $H\underline{r} = H\underline{e} = \underline{y}$
- Recover  $\underline{x}$  and sparse  $\underline{e}$

- $H\underline{s} = \underline{y}$
- Set  $\underline{r} = 0$  (Let a genie add  $\underline{x}$  to  $\underline{r}$ )
- $\underline{y}$  is given to the decoder
- Recover sparse  $\underline{s}$

## Application 2

# Sparse Fast Fourier Transform (SFFT) Computation

## Problem Statement

$x[n]$  : Time domain signal of length  $N$  whose spectrum is  $K$ -sparse

$$x[n] \xrightarrow{\text{DFT}} X[k]$$

( $K$ -sparse)

Compute the **locations** and **values** of the  $K$  non-zero coefficients w.h.p

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## Fast Fourier Transform (FFT)

- **Sample complexity**:  $N$  samples
- **Computational complexity**:  $O(N \log N)$

We want **sublinear** sample and computational complexity

# Sparse Fast Fourier Transform (SFFT) Computation

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Compute the **locations** and **values** of the  $K$  non-zero coefficients w.h.p

## Related work

- Spectral estimation - Prony's method
- More recently Pawar and Ramchandran'13, Hassanieh, Indyk, Katabi'12

# SFFT - A Sparse Graph Based Approach

## Main Idea - Pawar and Ramchandran 2013

- **Sub-sampling** in time corresponds to **aliasing** in frequency
- Aliased coefficients  $\Leftrightarrow$  parity check constraints of **GLDPC codes**
- **CRT** guided sub-sampling induces a code good for **Peeling decoder**
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## FFAST for Computing the DFT - Pawar and Ramchandran 2013

- **Sampling complexity:**  $M = O(K)$  time domain samples
- **Computational complexity:**  $O(K \log K)$

## Subsampling and Aliasing - A Quick Review

### Subsampling results in aliasing

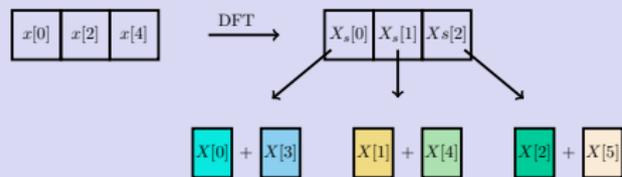
- Let  $x[n] \xrightarrow{N-DFT} X[k]$ ,  $k, n = 0, 1, \dots, N - 1$
- Let  $x_s[n] = x[mL]$ ,  $m = 0, 1, \dots, N/L = M$  be a sub-sampled signal
- Let  $x_s[m] \xrightarrow{M-DFT} X_s[l]$  be the DFT of the sub-sampled signal

$$X_s[l] = M \sum_{p=0}^{L-1} X[l + pM]$$

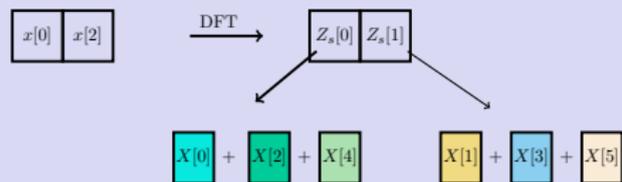
# Aliasing and Sparse Graph Codes



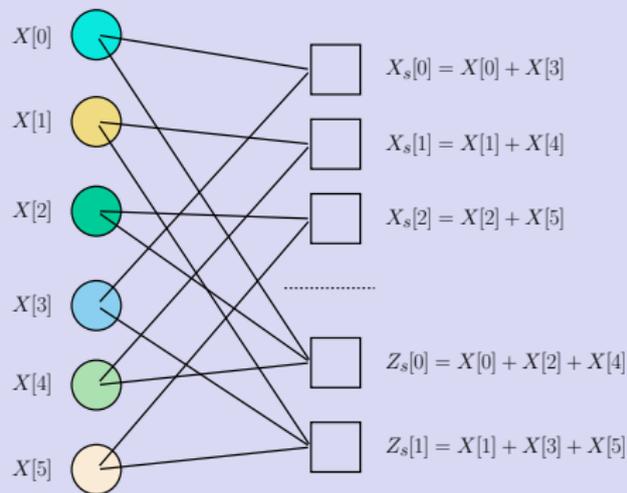
$x_s$ : Sub-sampled by  $f_1 = P_1 = 2$



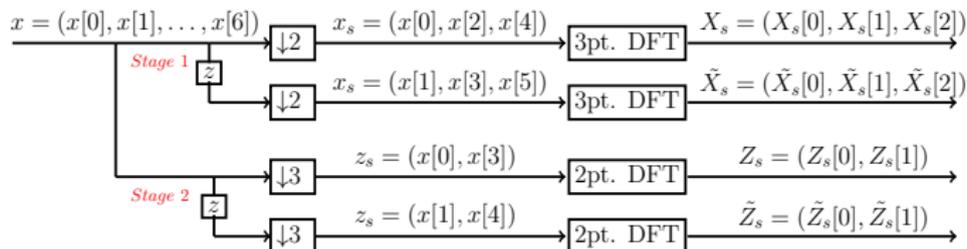
$z_s$ : Sub-sampled by  $f_2 = P_2 = 3$



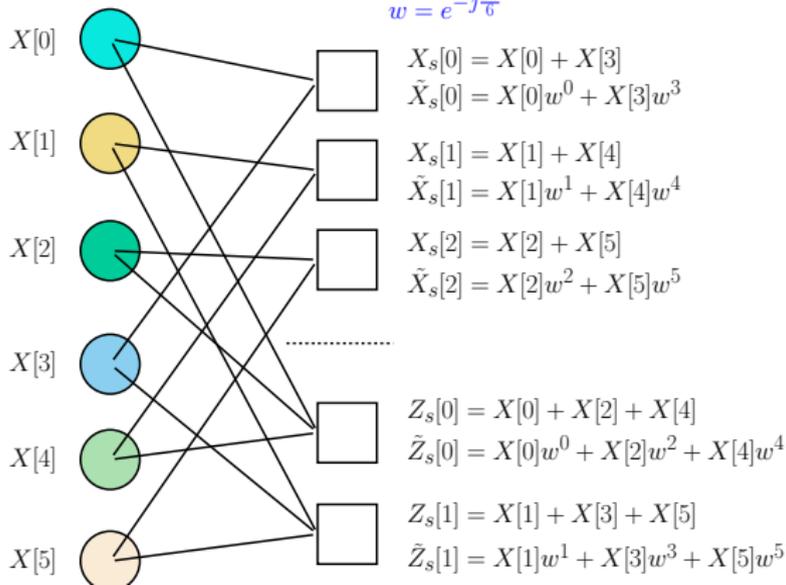
Factor graph



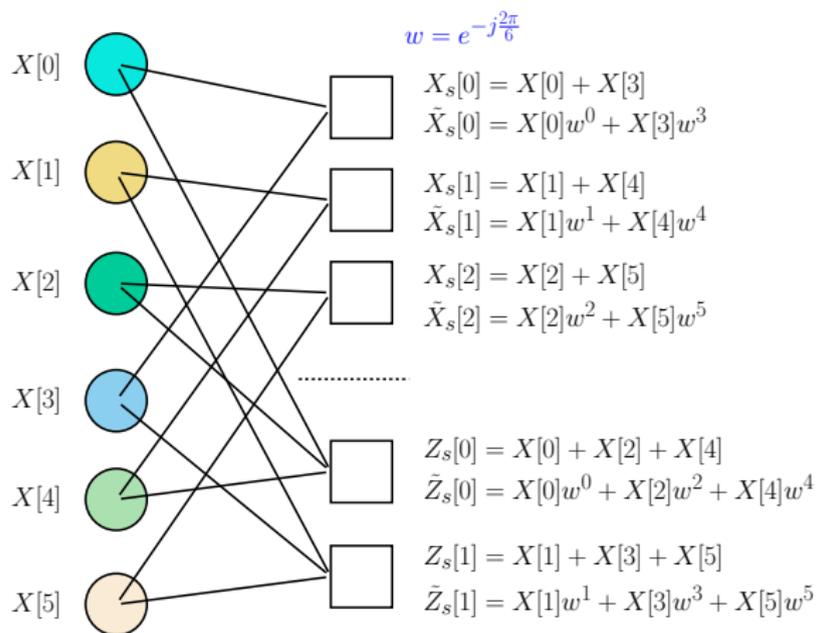
# FFAST Algorithm Example



$$w = e^{-j\frac{2\pi}{6}}$$



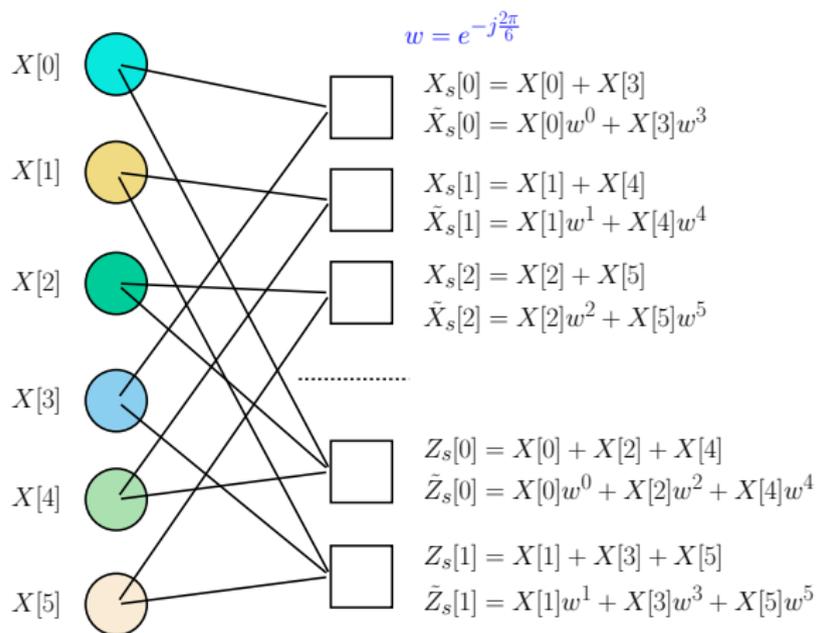
# Singleton Detection



## Singleton condition for a checknode

- Let  $i = \frac{-N}{j2\pi} \log\left(\frac{\tilde{X}_s[l]}{X_s[l]}\right)$ . If  $0 \leq i \leq N - 1$ , then checknode  $l$  is a **Singleton**.
- $Pos(l) = i$  is the only variable node participating and  $X_s[l]$  is its value.

# FFAST Decoder



## Peeling decoder

- 1 non-zero value among the neighbors of any right node can be recovered
- Iteratively errors can be corrected and analyzed for random non-zero coeffs

## FFAST Decoder Example

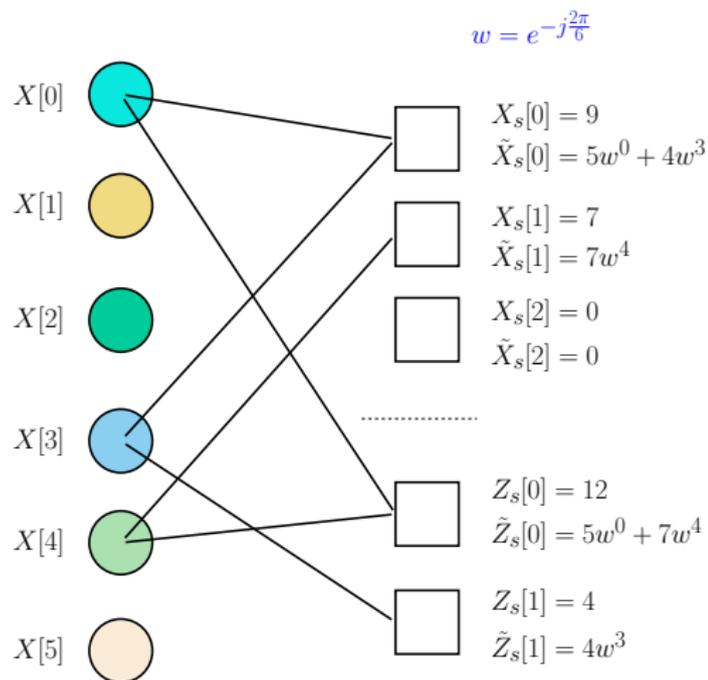
### Example 1

Let  $N = 6$ , and the non-zero coefficients be  $X[0]=5$ ,  $X[3]=4$ ,  $X[4]=7$

# FFAST Decoder Example

## Example 1

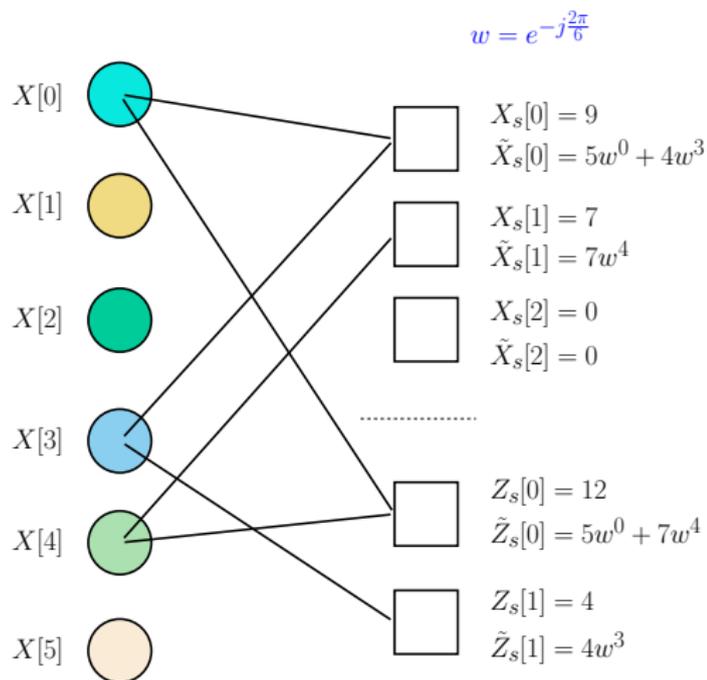
Let  $N = 6$ , and the non-zero coefficients be  $X[0]=5$ ,  $X[3]=4$ ,  $X[4]=7$



# FFAST Decoder Example

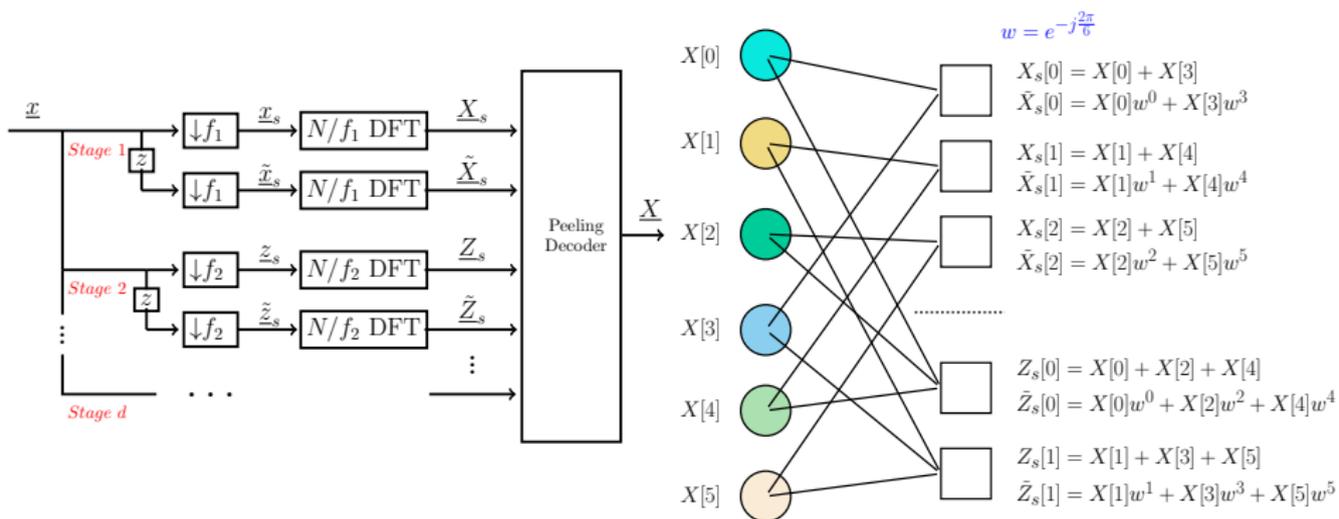
## Example 1

Let  $N = 6$ , and the non-zero coefficients be  $X[0]=5$ ,  $X[3]=4$ ,  $X[4]=7$



Yes, recoverable!

# Generalization



## Reed Solomon component codes

- $(X_s[l_1], \tilde{X}_s[l_1])$  correspond to 2 syndromes of a 1-error correcting RS code
- RS is over the complex field, no miscorrection

## Product codes and FFAST ( $d = 2$ )

- $X$ :  $K$ -sparse spectrum of length  $N = P_1 P_2$  ( $P_1$  and  $P_2$  are co-prime)
- $X'$ :  $P_1 \times P_2$  matrix formed by rearranging  $X$  according to mapping  $\mathcal{M}$

$$X_s[l_1] = \sum_{i=0}^{P_2-1} X[l_1 + iP_1], \quad 0 \leq l_1 \leq P_2 - 1$$
$$Z_s[l_2] = \sum_{i=0}^{P_1-1} X[l_2 + iP_2], \quad 0 \leq l_2 \leq P_1 - 1$$

### Mapping

The mapping from  $X(r)$  to  $X'(i, j)$  is given by

$$(i, j) = \mathcal{M}(r) \equiv (r \bmod P_2, r \bmod P_1).$$

**Note:** CRT ensures that  $\mathcal{M}$  is **bijjective**

	$Z_s[0]$	$Z_s[1]$	$Z_s[2]$	$Z_s[3]$
$X_s[0] \rightarrow$	$X[0]$	$X[5]$	$X[10]$	$X[15]$
$X_s[1] \rightarrow$	$X[16]$	$X[1]$	$X[6]$	$X[11]$
$X_s[2] \rightarrow$	$X[12]$	$X[17]$	$X[2]$	$X[7]$
$X_s[3] \rightarrow$	$X[8]$	$X[13]$	$X[18]$	$X[3]$
$X_s[4] \rightarrow$	$X[4]$	$X[9]$	$X[14]$	$X[19]$

## Product codes and FFAST ( $d \geq 3$ )

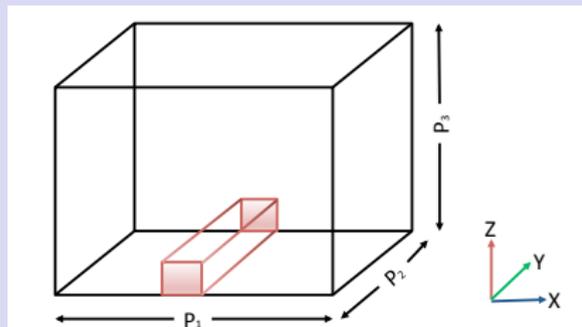
$$N = P_1 \times P_2 \times \dots \times P_d$$

$$(i_1, i_2, \dots, i_d) = \mathcal{M}(r) \equiv (r \bmod f_1, r \bmod f_2, \dots, r \bmod f_d).$$

Less-sparse regime

$$f_i = N/P_i, \quad i = 1, 2, \dots, d$$

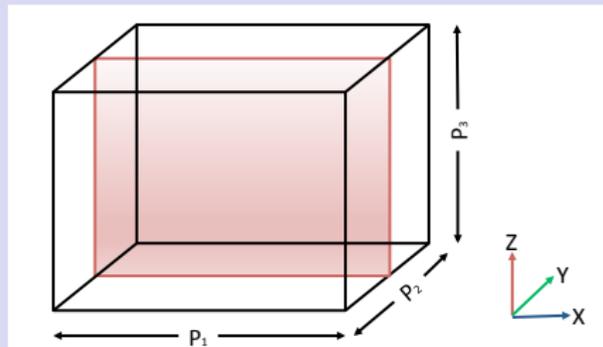
$$d = 3$$



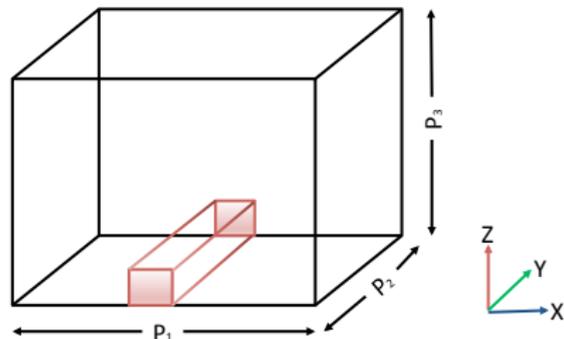
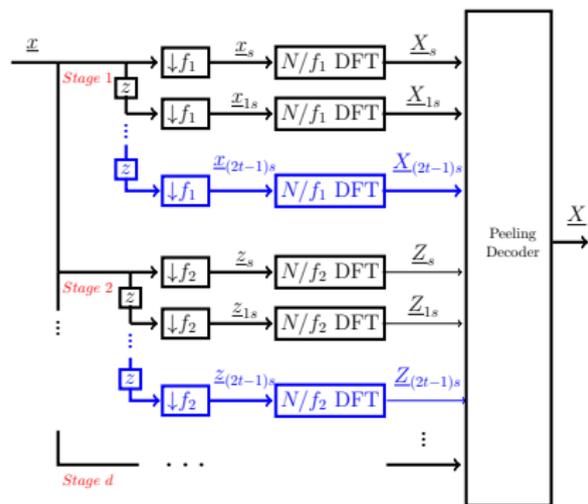
Very-sparse regime

$$f_i = P_i, \quad i = 1, 2, \dots, d$$

$$d = 3$$



# Connections between FFAST and Product Codes



FFAST	⇔	Product codes
$d$ stages	⇔	$d$ -dimensional product code
$2t$ branches	⇔	$t$ -error correcting RS component codes
Non-zero coefficients	⇔	Error locations
Recovery of coefficients	⇔	Iterative decoding

# Thresholds

## Theorem 1

*Less sparse case: In the limit of large  $P$ , the FFAST algorithm with  $d$  branches and  $2t$  stages can recover the FFT coefficients w.h.p if  $K < \frac{2dt}{c_{d,t}}$ .*

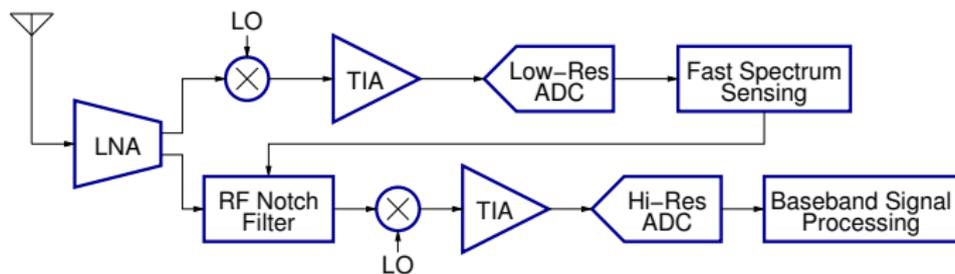
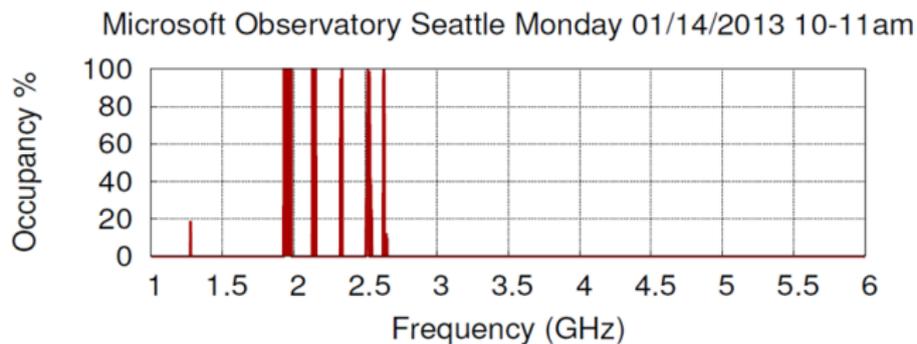
$$c_{d,t} = \min_m \{m/\pi^{d-1}(m)\}$$

$$\text{Threshold} = \frac{\# \text{ of measurements}}{\text{recoverable sparsity}} = \frac{2dt}{c_{d,t}}$$

	$d = 2$	$d = 3$	$d = 4$	$d = 5$	$d = 6$	$d = 7$	$d = 8$
$t = 1$	4.0	2.4436	2.5897	2.8499	3.1393	3.4378	3.7383
$t = 2$	2.3874	2.5759	2.9993	3.4549	3.9153	4.3736	4.8278
$t = 3$	2.3304	2.7593	3.3133	3.8817	4.4483	5.0094	5.5641
$t = 4$	2.3532	2.9125	3.5556	4.2043	4.8468	5.4802	6.1033

Notice that  $L, K = O\left(N^{\frac{1-d}{d}}\right)$

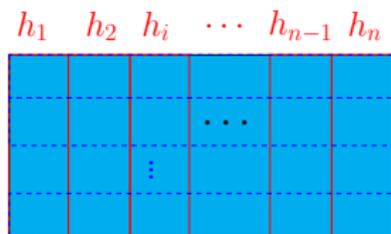
# Interference-tolerant A/D Converter



# Open problems

- If we use MAP decoding, is the subsampling procedure optimal?
- What happens when  $N = 2^i$  ?
- Bursty case? Can we have threshold theorems?
- Using this idea in actual applications

# Syndromes and decoding



$H_{m \times n}$   
(Parity checks)

$\times$



$c_{n \times 1}$   
(code vector)

$+$



$e$   
(error vector)  
 $t$ -sparse

$=$

$0$   $+$



$y_{m \times 1}$   
Syndromes





# Syndrome source coding

$$H_{m \times n} \times x = y_{m \times 1}$$

$H_{m \times n}$   
(Parity check matrix)

$x$   
(Source vector)  
 $t$ -sparse

$y_{m \times 1}$   
Syndromes

## Compression of a sparse binary source

- Compressed version is the syndrome  $\underline{y}$
- Reconstruction is the same as decoding
- Similar to the canonical sparse recovery problem

# Review of primitives

- Idea of a check node or a measurement node which is a function of some symbols
- Singleton detection - be able to identify one non-zero symbol
- Peeling - if we know some symbols, be able to remove and adjust measurement

# Application 3

# Compressed sensing

$y_{m \times 1}$   
(observations)

$A_{m \times n}$   
( $m \ll n$ )

$x_{n \times 1}$   
( $K$ -sparse)

## Classical compressed sensing

- $\underline{x}$  is a  $K$ -sparse vector over  $\mathbb{R}$  or  $\mathbb{C}$
- We 'compress'  $\underline{x}$  by storing only  $\underline{y} = \mathbf{A} \underline{x}$
- Reconstruction - Solve  $\hat{\underline{x}} = \arg \min \|\underline{z}\|_0 : \underline{y} = \mathbf{A} \underline{z}$
- CS - Solve  $\hat{\underline{x}} = \arg \min \|\underline{z}\|_1 : \underline{y} = \mathbf{A} \underline{z}$

# Compressed sensing

$$\begin{matrix} \begin{matrix} \square \\ \square \\ \vdots \\ \square \end{matrix} \\ y_{m \times 1} \\ \text{(observations)} \end{matrix} = \begin{matrix} \begin{matrix} \square & a_1 \\ \square & a_2 \\ \square & \vdots \\ \square & a_m \end{matrix} \\ A_{m \times n} \\ (m \ll n) \end{matrix} \times \begin{matrix} \begin{matrix} \square \\ \square \\ \square \\ \square \\ \square \\ \square \\ \square \end{matrix} \\ x_{n \times 1} \\ \text{(K-sparse)} \end{matrix}$$

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## Coding theoretic approach - syndrome source coding over complex numbers

- Sensing matrix  $\mathbf{A} \Leftrightarrow$  Parity check matrix  $\mathbf{H}$

# Data stream computing

Problem - consider a router in a large network

- Count the number of packets from source  $i$  to destination  $j$ , say  $x_{ij}$
- Data vector is huge,  $n = 2^{64}$
- Heavy hitters - only a few of them are large

$y_{m \times 1}$   
(sketch of  $x$ )

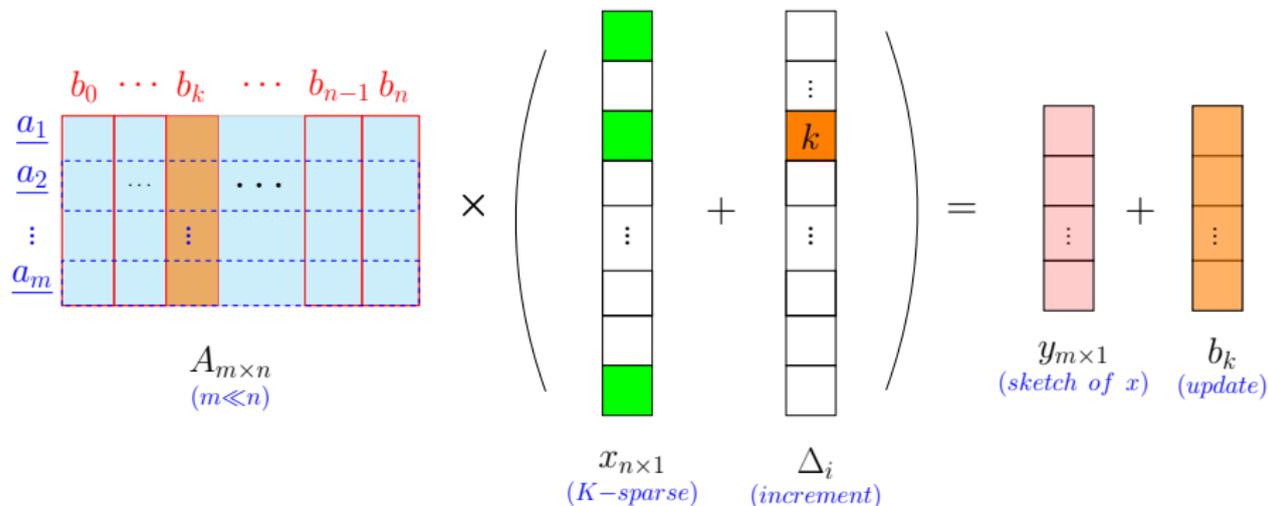
$A_{m \times n}$   
( $m \ll n$ )

$x_{n \times 1}$   
( $K$ -sparse)

Keep only a low dimensional ( $m \ll n$ ) sketch of  $x$

- $\underline{y}_{m \times 1} = \underline{A} \underline{x} \Leftrightarrow$  Syndrome,  $x_{i,j} \in \mathbb{Z}^+$
- Reconstruction is same as decoding

# Incremental updates

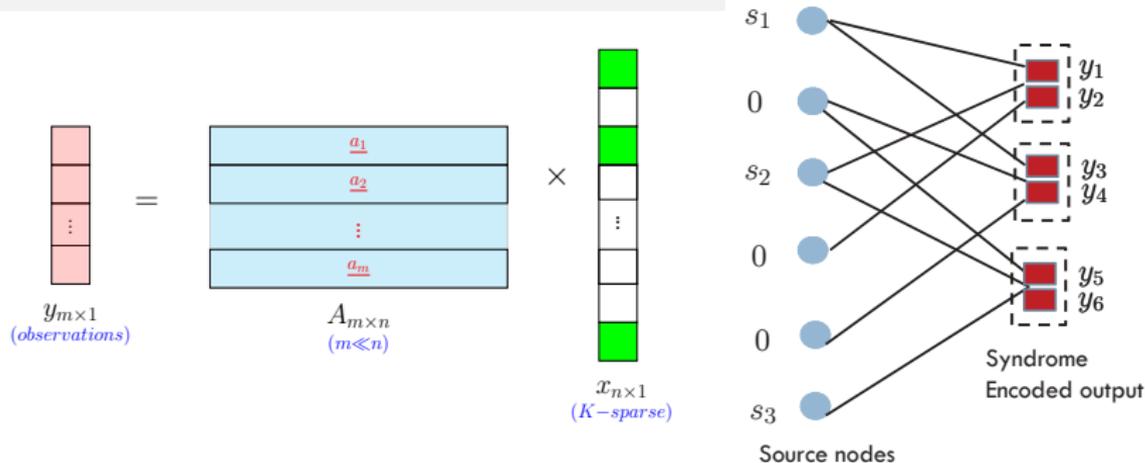


Sketch  $y$  supports incremental updates to  $x$  as the sketching procedure is linear.

$$x + \Delta_i \rightarrow y + A\Delta_i$$

(adding  $i$ th column vector of  $A$  to existing sketch)

# Compressed Sensing (Li, Ramchandran '14)



Sketching matrix ( $A_{m \times n}$ )

$$A_{m \times n} = \mathbf{H}_{\frac{m}{2} \times n} \otimes \mathbf{B}_{2 \times n}$$

(*d-left regular Graph*)      (*Singleton identifier*)

$$\mathbf{B} = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & W & W^2 & \dots & W^{n-1} \end{bmatrix} \quad W = e^{j \frac{2\pi}{n}}$$

# Main results for compressed sensing

## Noiseless case

- Samples :  $2K$  versus Info-theoretic limit  $K + 1$
- Computations:  $O(K)$  versus  $O(K^2)$
- If  $K = O(n^\delta)$ , small price to pay in terms of samples

## Noisy case

- Sample:  $O(k \log^{1.3} n)$  vs limit:  $O(k \log(n/k))$  necessary and sufficient
- Computations:  $O(k \log^{1.3} n)$

# Main results for compressed sensing

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## Vem, Thenkarai Janakiraman, N. ITW'16

- Sample:  $O(k \log^{1.3} (n/k))$  vs limit:  $O(k \log(n/k))$  necessary and sufficient
- Computations:  $O(k \log^{1.3} (n/k))$

## Group Testing (Lee, Pedarsani, Ramchandran '15)



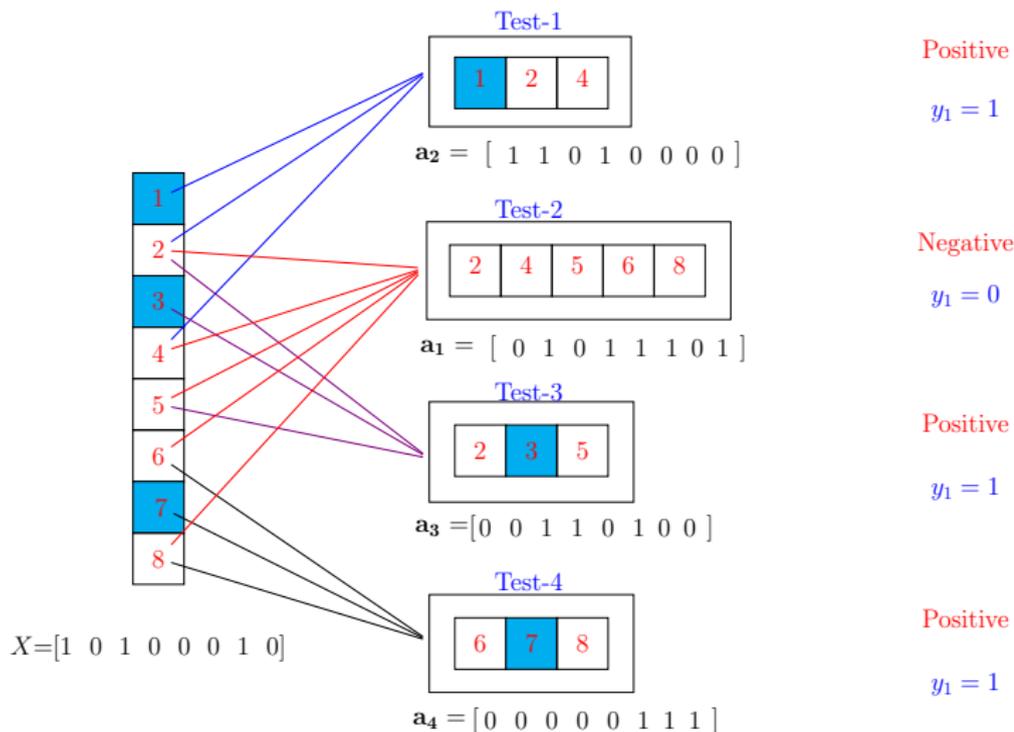
- II World War - detect all soldiers with syphilis
- Tests performed on efficiently pooled groups of items
- Least no. of tests ( $m$ ) to identify  $k$  defective items from  $n$  items

# Group Testing

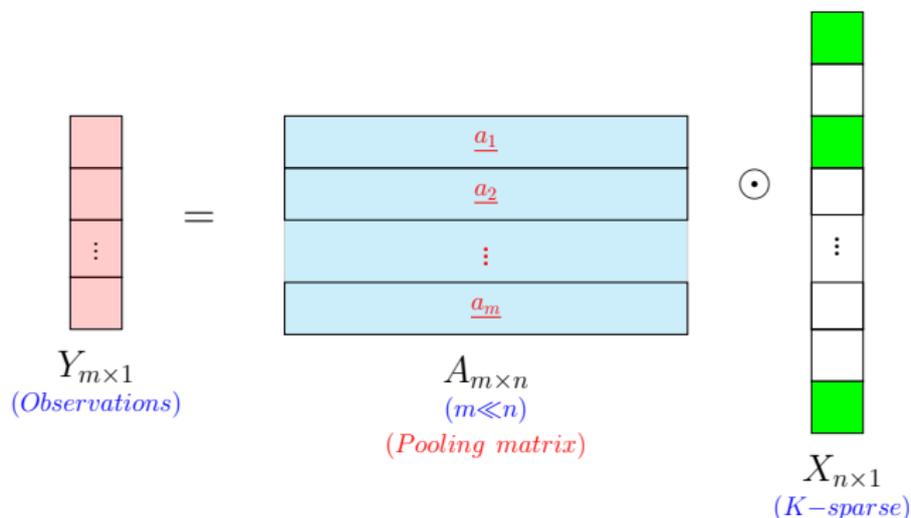
## Example

Test Results (Observations)

$$y_i = \bigvee_{j=1}^N a_{ij} X_j = \langle a_i, X \rangle$$



# Group Testing



$$Y_{m \times 1} \text{ (Observation vector)} = A \odot X = \begin{bmatrix} \langle a_1, X \rangle \\ \langle a_2, X \rangle \\ \vdots \\ \langle a_m, X \rangle \end{bmatrix} \quad \langle a_i, X \rangle = \bigvee_{j=1}^N a_{ij} X_j$$

# Group Testing

## Singleton detection

$$\begin{bmatrix} H_1 \\ \overline{H_1} \end{bmatrix} = \begin{bmatrix} b_1 & b_2 & b_3 & \dots & b_{n-1} \\ \overline{b_1} & \overline{b_2} & \overline{b_3} & \dots & \overline{b_{n-1}} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & \dots & 1 & 1 \\ 0 & 0 & 0 & \dots & 1 & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 1 & \dots & 1 & 1 \\ 0 & 1 & 0 & \dots & 0 & 1 \\ \hline 1 & 1 & 1 & \dots & 0 & 0 \\ 1 & 1 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 1 & 0 & \dots & 0 & 0 \\ 1 & 0 & 1 & \dots & 1 & 0 \end{bmatrix}$$

**Note:** If a checknode is a singleton, with  $i$ th bit-node participating, then the observation vector is the  $i$ th column of  $A$ .

- Singleton - if the **weight of first two observation** vectors together is  $L$ .
- **Position** of the defective item is - **decimal value of the 1st observation vector**.

# Group Testing

Measurement matrix ( $A_{m \times n}$ )

$$A_{m \times n} = \mathbf{G}_{\frac{m}{6} \times n} \otimes \mathbf{H}_{6 \times n}$$

*(d-left regular Graph) (Singleton identifier)*

Let,  $\mathbf{b}_i$  denote the  $L$ -bits binary representation of the integer  $i - 1$ ,  $L = \lceil \log_2 n \rceil$ .

$$H = \begin{bmatrix} \mathbf{b}_1 & \mathbf{b}_2 & \mathbf{b}_3 & \cdots & \mathbf{b}_{n-1} \\ \mathbf{b}_1 & \mathbf{b}_2 & \mathbf{b}_3 & \cdots & \mathbf{b}_{n-1} \\ \mathbf{b}_{i_1} & \mathbf{b}_{i_2} & \mathbf{b}_{i_3} & \cdots & \mathbf{b}_{i_{n-1}} \\ \mathbf{b}_{i_1} & \mathbf{b}_{i_2} & \mathbf{b}_{i_3} & \cdots & \mathbf{b}_{i_{n-1}} \\ \mathbf{b}_{j_1} & \mathbf{b}_{j_2} & \mathbf{b}_{j_3} & \cdots & \mathbf{b}_{j_{n-1}} \\ \mathbf{b}_{j_1} & \mathbf{b}_{j_2} & \mathbf{b}_{j_3} & \cdots & \mathbf{b}_{j_{n-1}} \end{bmatrix}$$

$s_1 = (i_1, i_2, \dots, i_{n-1})$  and  $s_2 = (j_1, j_2, \dots, j_{n-1})$  are permutations

Decoding procedure

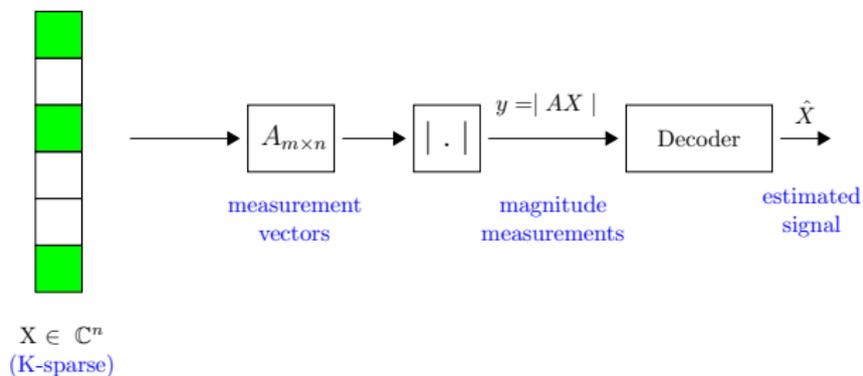
- Identify and decodes singletons using weights of the observation vector
- Identify and resolve doubletons by guessing to satisfy the first pair of observation vectors and checking if the guess satisfies the other two pairs of observations

# Main results for group testing

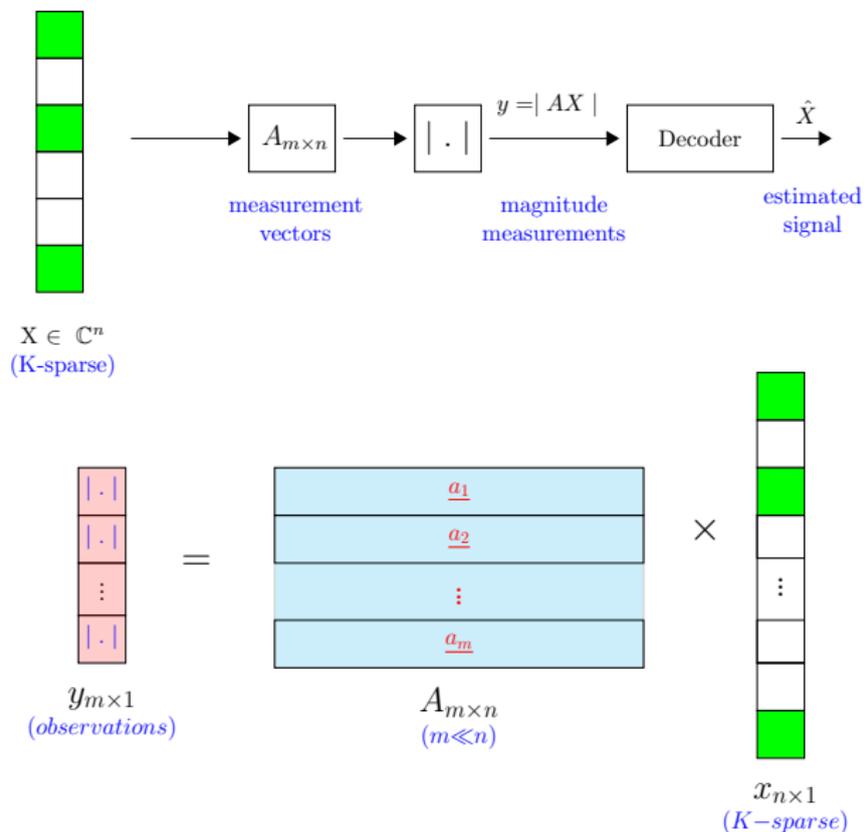
## Non-adaptive Group Testing (Noiseless and Noisy)

- Recovers  $(1 - \epsilon)k$  items with h.p.
- Samples:  $m = O(k \log_2 n)$  versus limit:  $\Theta(k \log(\frac{n}{k}))$
- Computational complexity:  $O(k \log n)$  (order optimal)

# Compressive Phase Retrieval



# Compressive Phase Retrieval



# Conclusion

- Review of a simple message passing decoder called the peeling decoder
- Density evolution as a tool to analyze its asymptotic performance
- Applications
  - Massive uncoordinated multiple access
  - Sparse Fourier transform computation
  - Compressed sensing type sparse recovery problems

Questions?



Thank you!