

Optimizing Degree Distributions of LT-based Codes With Deep Reinforcement Learning

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Outline

- 1) Brief Introduction
- 2) Motivation, Objective and Challenges
- 3) Our Method
- 4) Evaluation
- 5) Conclusion

Fountain coding for networking

Digital Fountain (DF) protocol vs TCP

- 1) Digital Fountain protocol is used as a rateless erasure codes
- 2) Digital Fountain(DF) protocols internally use Fountain codes;
- 3) DF protocol ensures reliability and allows full use of all available bandwidth regardless of network congestion, packet loss, or latency;
- 4) It overcomes TCP's bandwidth inefficiencies by providing an alternative way to reliably transfer data over an IP network.

Notable examples: DF Raptor and RaptorQ

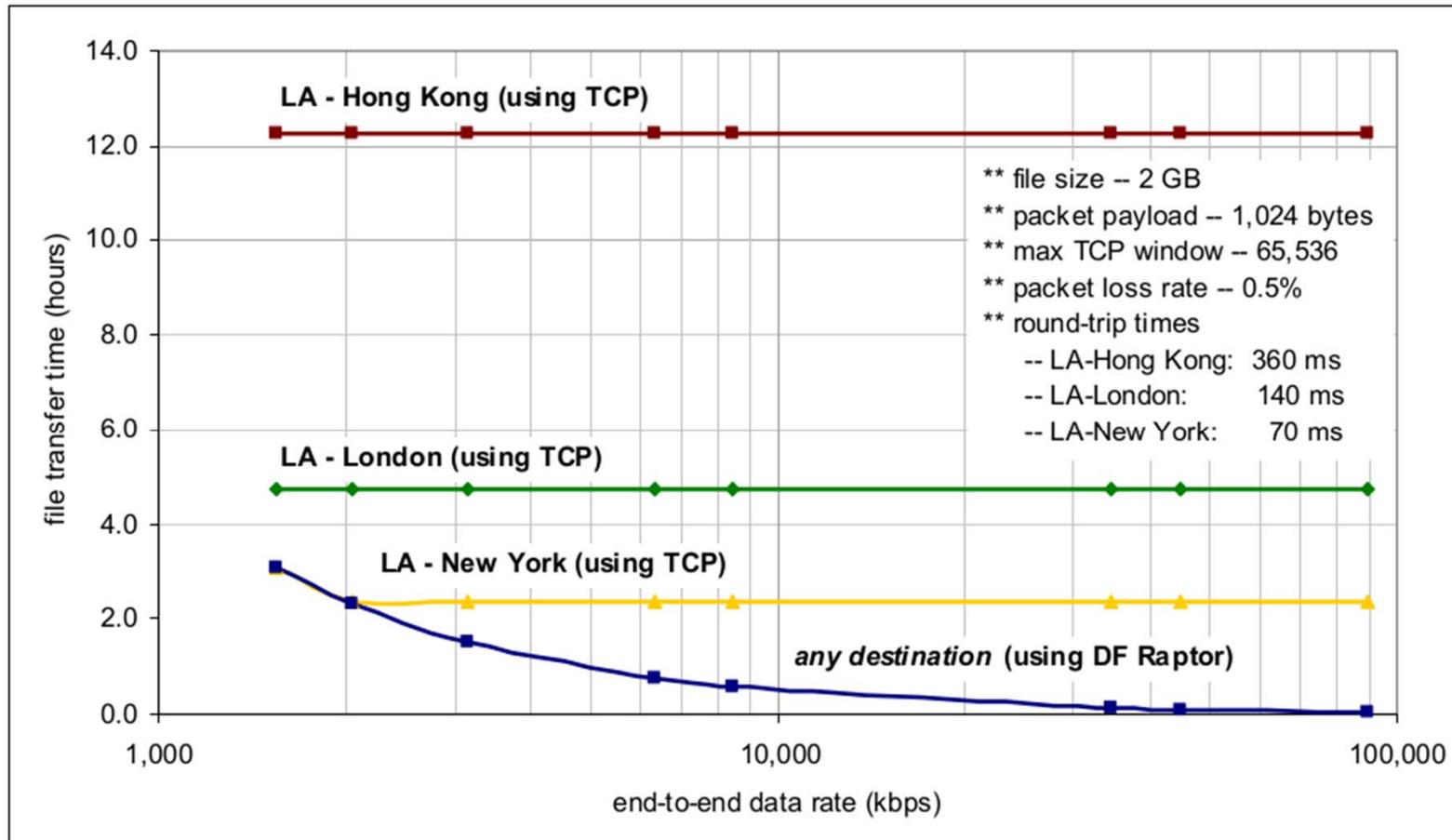
Forward error correction technologies

Raptor and RaptorQ Forward error correction technologies

- 1) Accelerate transfer time
- 2) Efficient bandwidth utilization
- 3) Ensured reliability
- 4) Reduced cost – better use of network resources
- 5) Adaptability to changing network conditions
- 6) Minimum processing requirements

Specific Practical Example

One-To-One Transmission Over Large Distances



- 1) DF Raptor FEC can take full advantage of the available bandwidth in transferring a 2GB file,
- 2) while TCP incurs long transfer times that reflect the round-trip time to the destination

How It Works ?

- DF protocol is usually built on top of UDP.
- UDP, which is a connectionless protocol, neither consumes bandwidth with acknowledgements and re-transmissions nor restricts the amount of data that can be transmitted.
-
- UDP packets are encoded by using so called ***fountain codes***, which are rateless erasure codes, and transmitted to the receivers equipped with appropriate decoders.
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More Information About Application to Networking

- Many real world applications can be found at
- <https://www.qualcomm.com/products/wi-fi>
-
- IETF | RFCs documents:
- <https://tools.ietf.org/html/rfc6330> (RaptorQ)
- <https://tools.ietf.org/html/rfc5053> (Raptor)
-
- Digital Fountain Based Communication:
- <https://ieeexplore.ieee.org/document/6918262>
- <https://ieeexplore.ieee.org/document/7417127>
- <https://ieeexplore.ieee.org/document/6663513>
- <https://ieeexplore.ieee.org/document/5279383>
- <https://ieeexplore.ieee.org/document/6959244>
- <https://ieeexplore.ieee.org/document/4675714>
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- “Enhancing communications with RaptorQ”
- <https://www.codornices.info>



Motivation

- LT codes are first practical fountain codes, proposed by Michael Luby.
- Raptor, RaptorQ, Zigzag Decodable fountain codes are all the extensions of LT codes. Further, we refer to them (including LT codes) as LT-based codes.
- The key component of those codes is the so-called **degree distribution** used in the encoding procedure.
- The degree distribution is the important component responsible for the efficiency of those codes.
- Therefore optimization and customization for particular applications is necessary, but it is not straightforward.



Objective

- Recent success in deep learning area motivates seeking its applications.
- We, in particular, are interested in possible applications of deep learning to the coding theory.
- Certainly, deep learning can not be applied to channel coding directly due to the strict demand on latency and throughput; therefore, we consider its application for optimizations of existing coding mechanisms.
- In this work, we try to optimize degree distributions by using deep reinforcement learning techniques, which to a certain extent overcome the *"curse of dimensionality"*.

Coding Scheme (1): Encoding

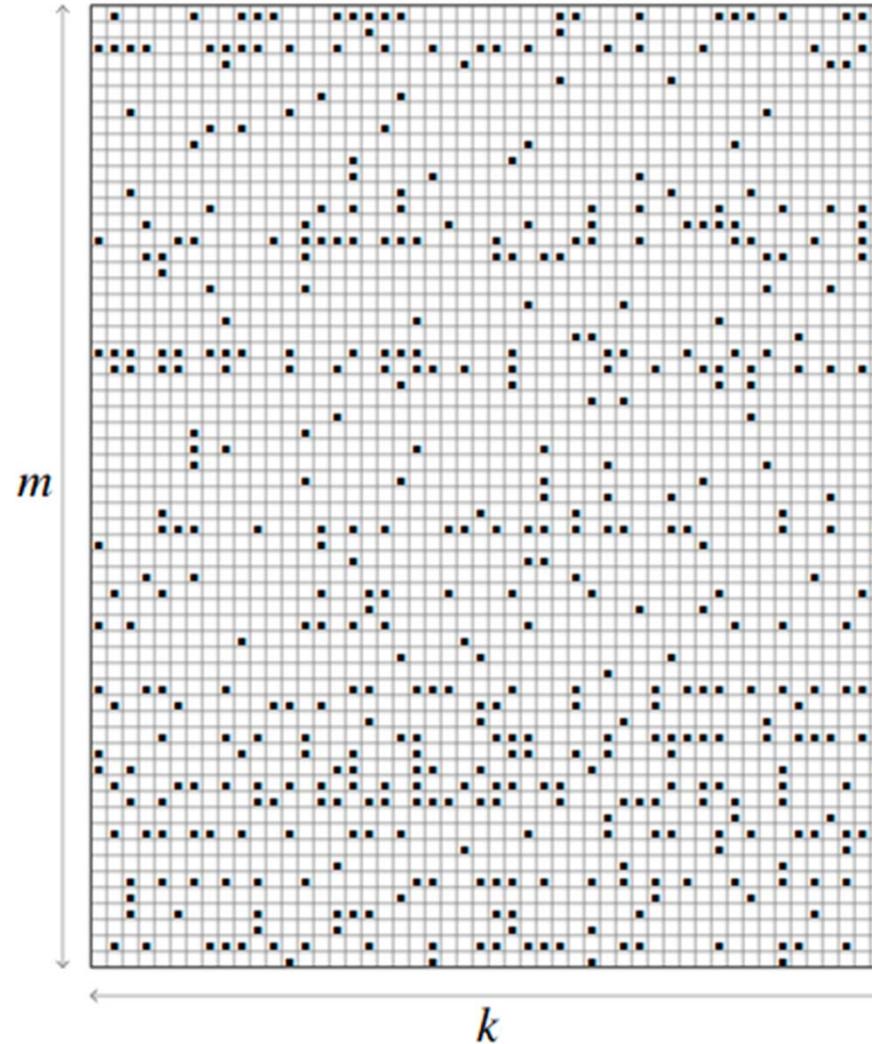
LT codes with Inactivation decoding

- Randomly choose the degree d of the encoding symbol from a degree distribution.
- Choose uniformly at random d distinct input symbols as neighbors of the encoding symbol.
- The value of the encoding symbol is the exclusive-or of the d neighbors.
-
- ***Note, packet-level encoding is done by concatenating the symbols into a string and performing the same operations on the elements of the string as would be performed on 1-bit symbol.***

Coding Scheme (2): Decoding

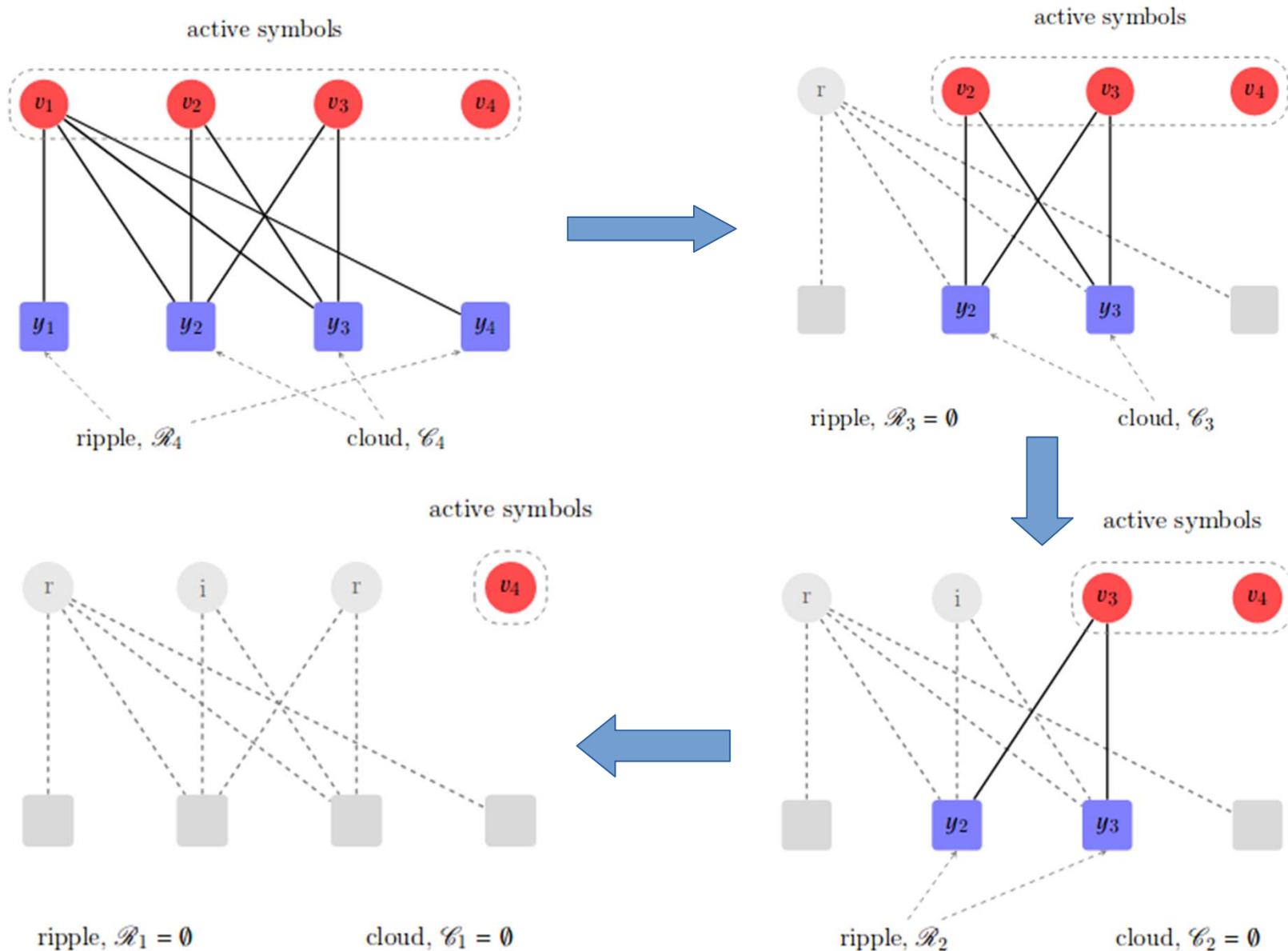
LT codes with Inactivation decoding

Generator matrix



Coding Scheme (3): Decoding

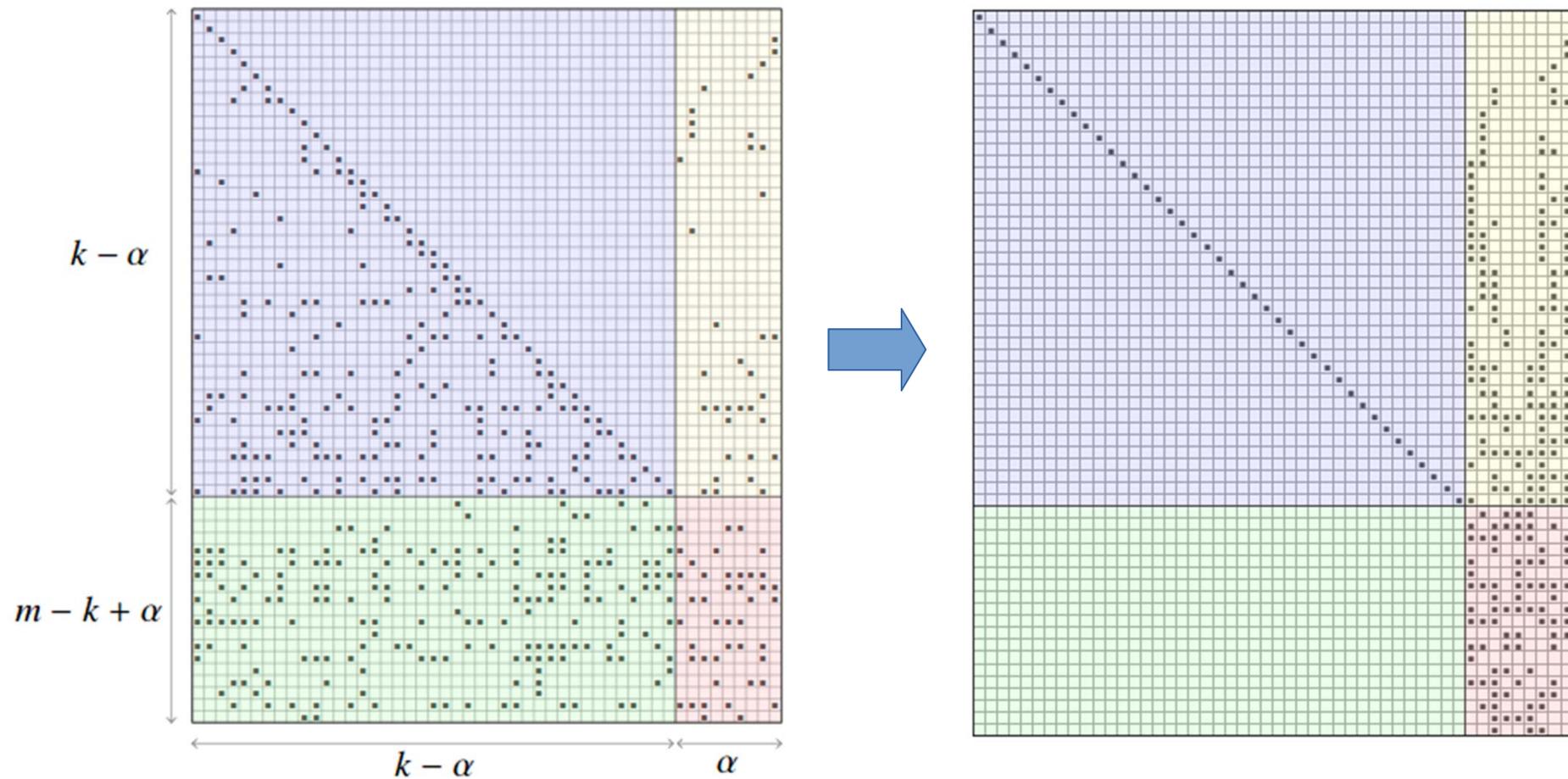
LT codes with Inactivation decoding



Coding Scheme (4): Decoding

LT codes with Inactivation decoding

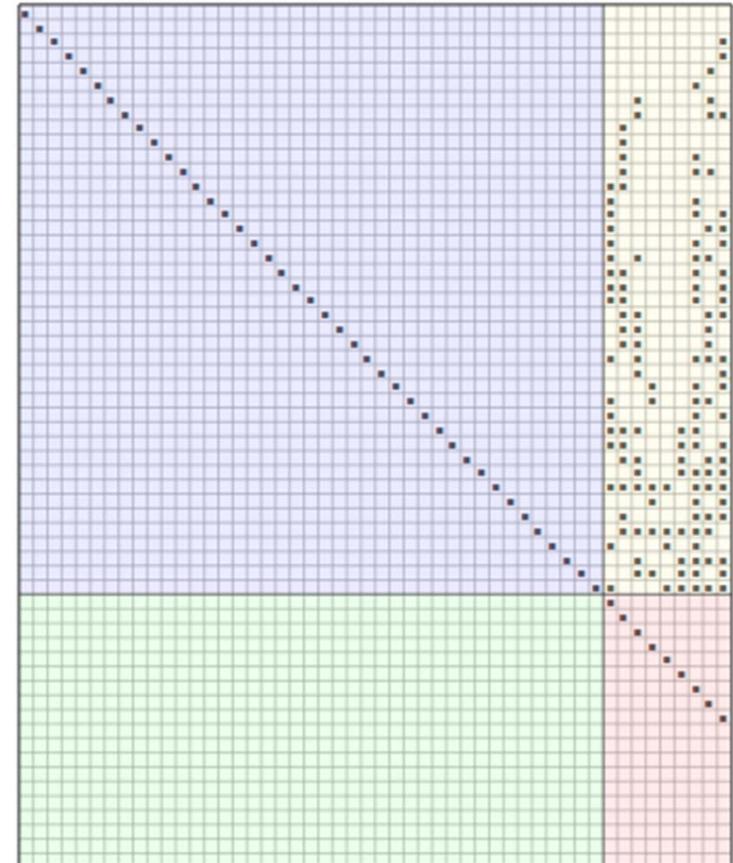
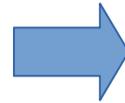
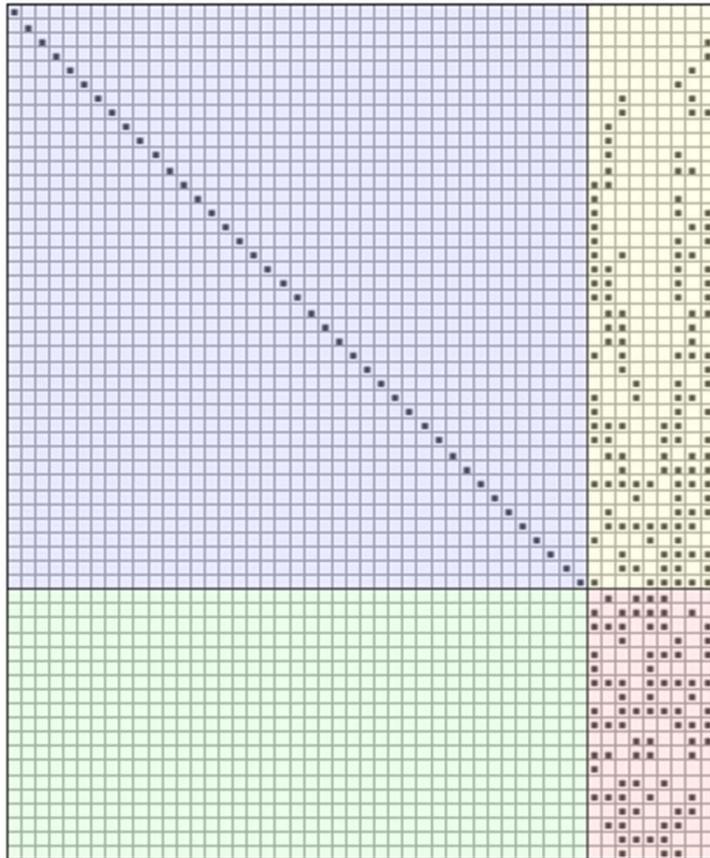
ZERO MATRIX PROCEDURE



Coding Scheme (5): Decoding

LT codes with Inactivation decoding

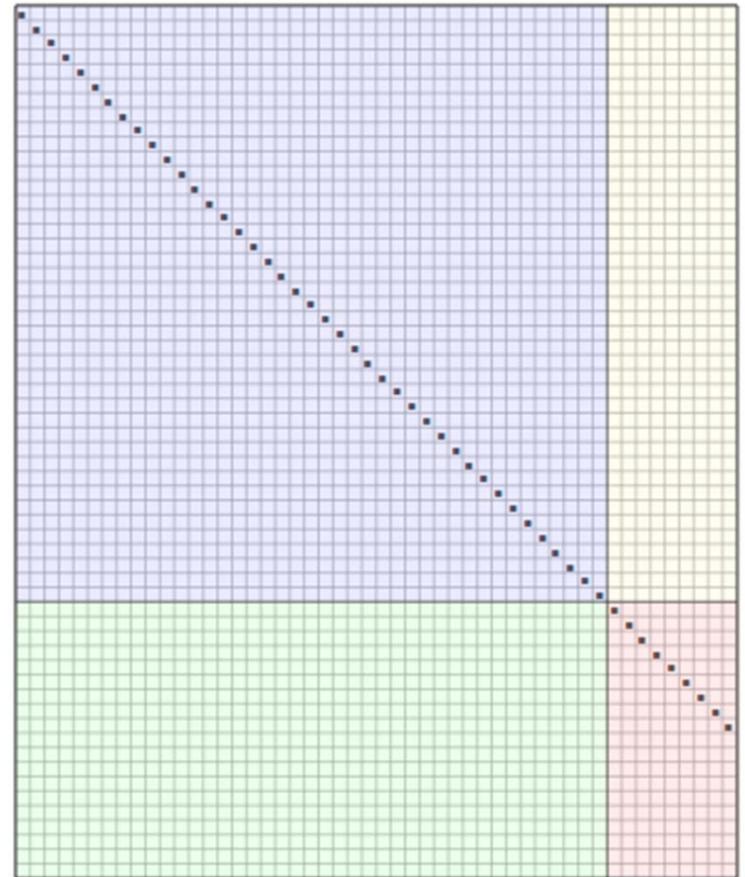
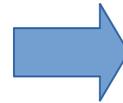
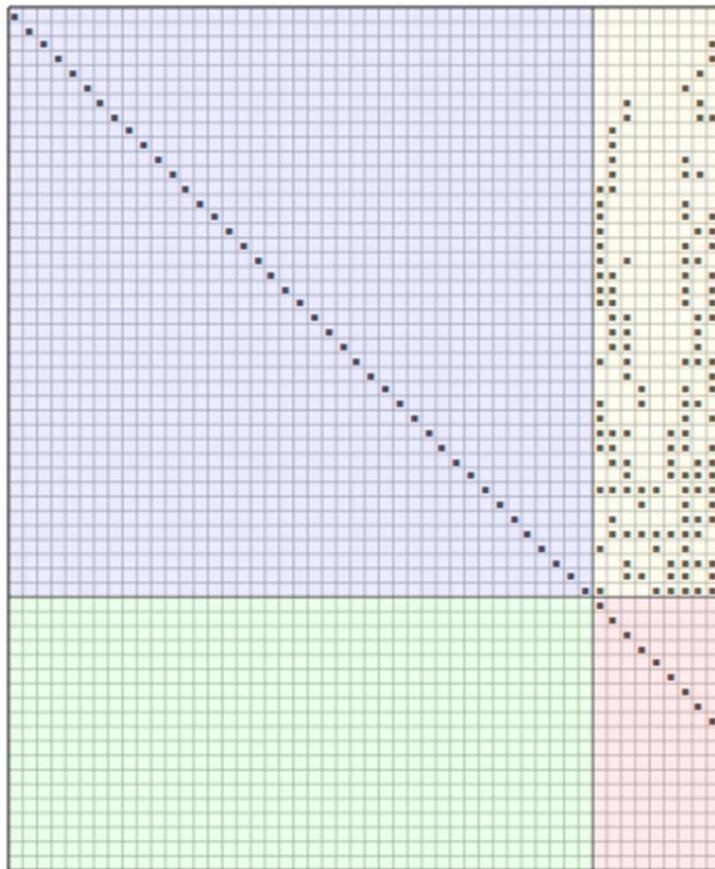
GAUSSIAN ELIMINATION



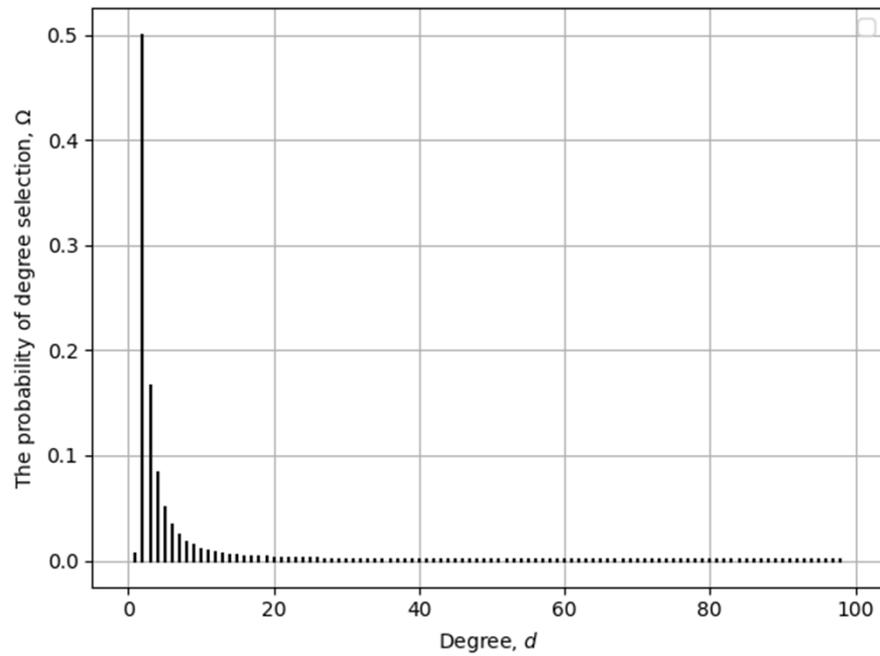
Coding Scheme (6): Decoding

LT codes with Inactivation decoding

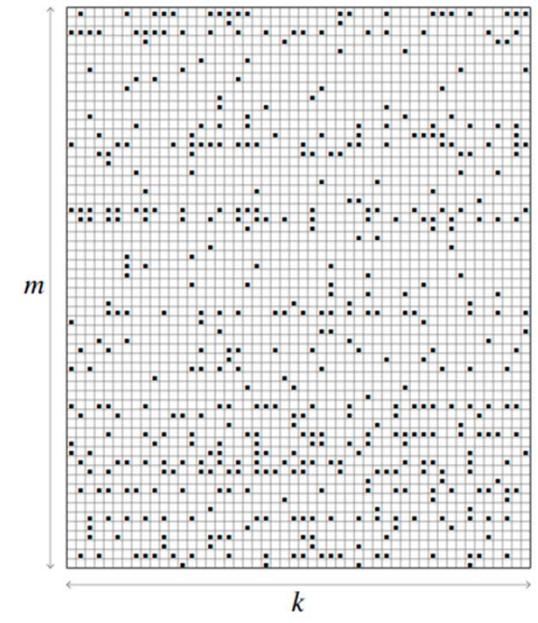
BACK SUBSTITUTION



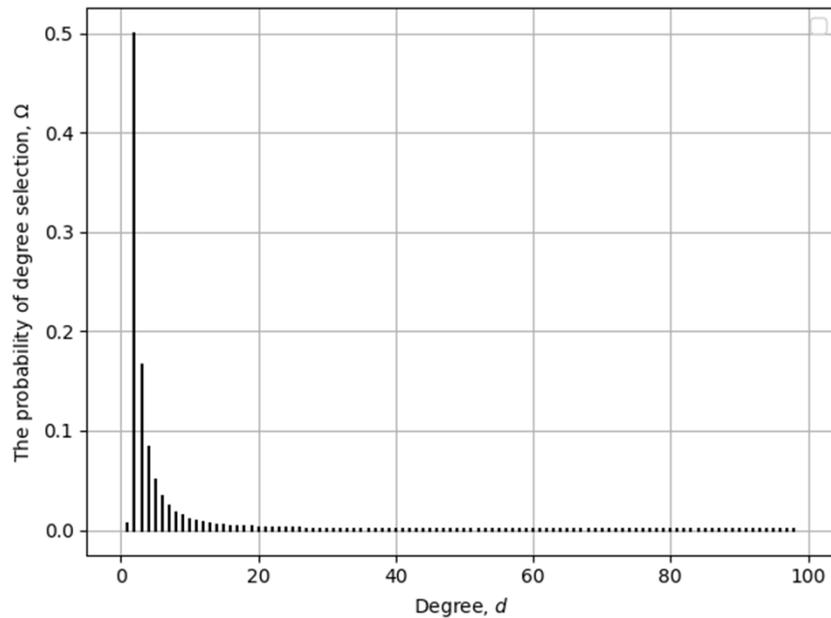
Degree distribution matters



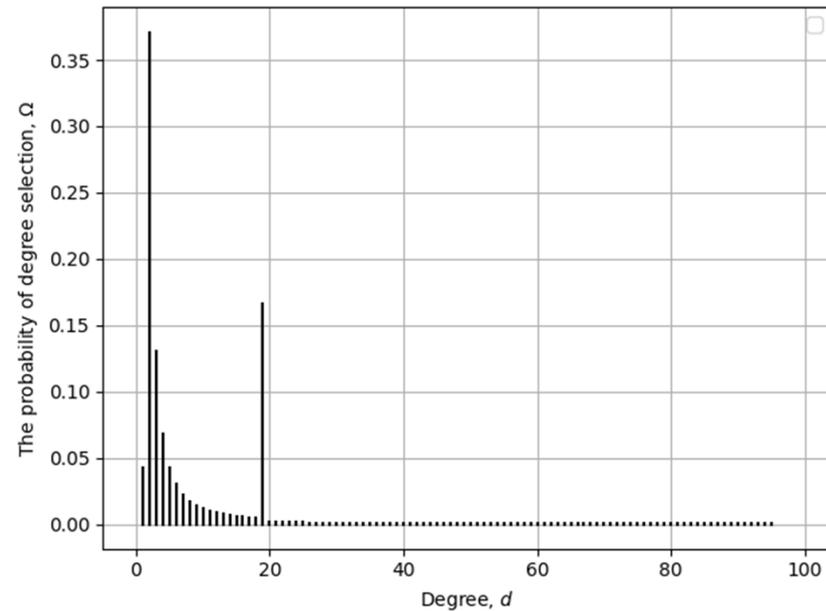
DEFINES



Classical Degree Distributions



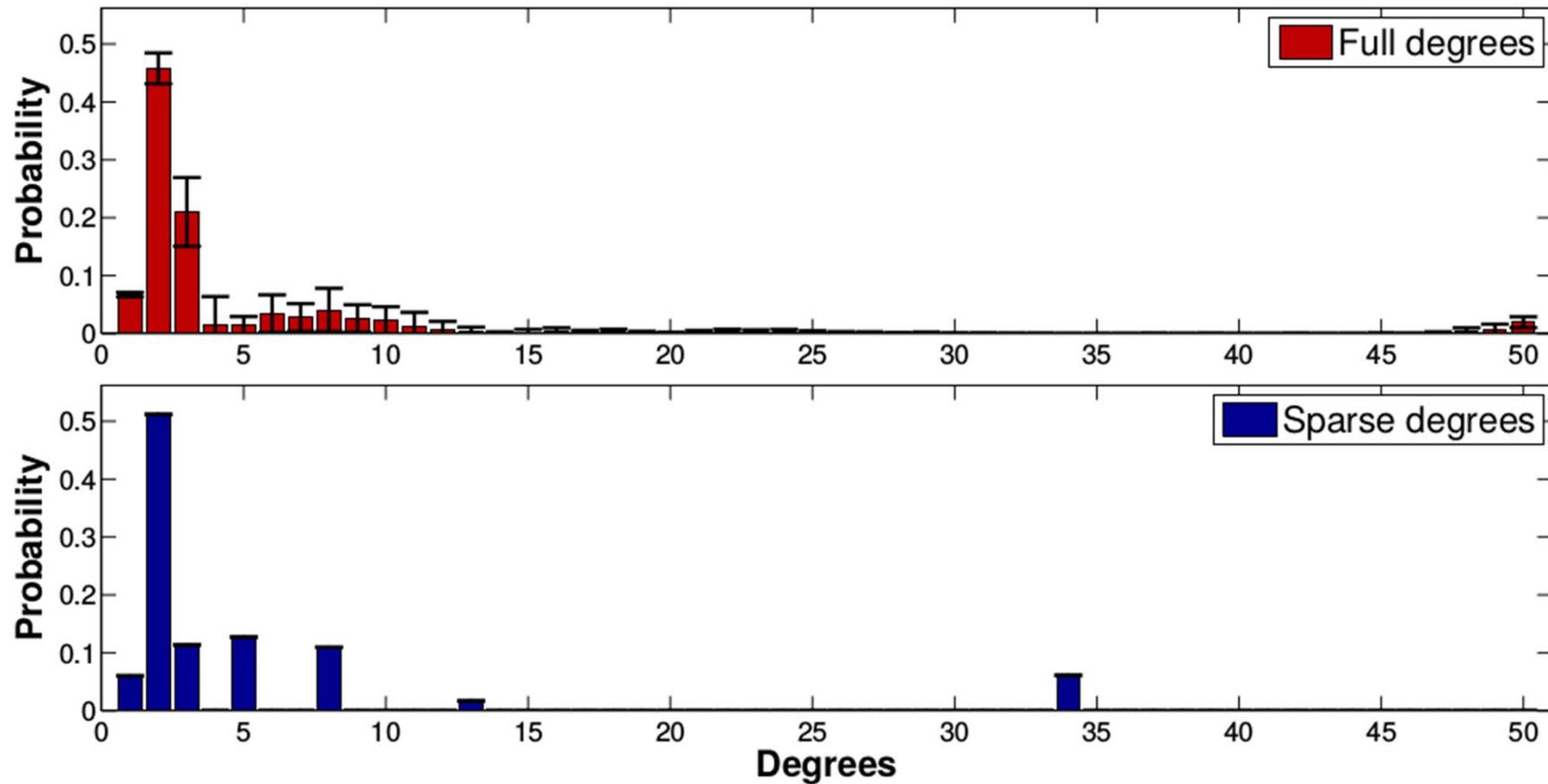
Ideal Soliton Degree Distribution



Robust Soliton Degree Distribution

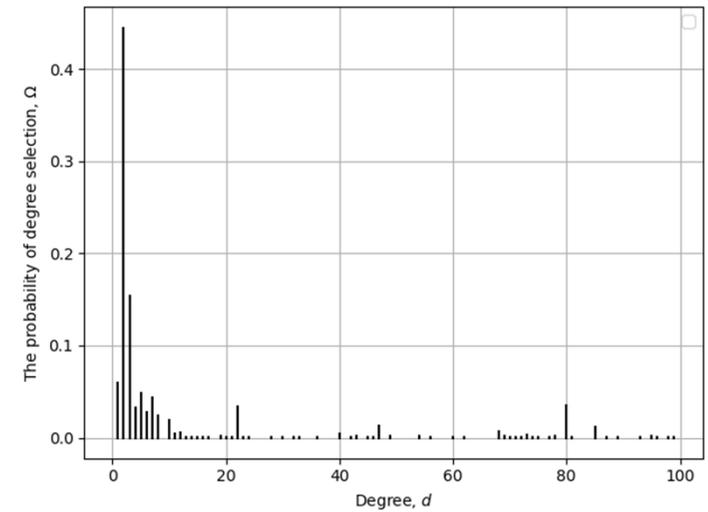
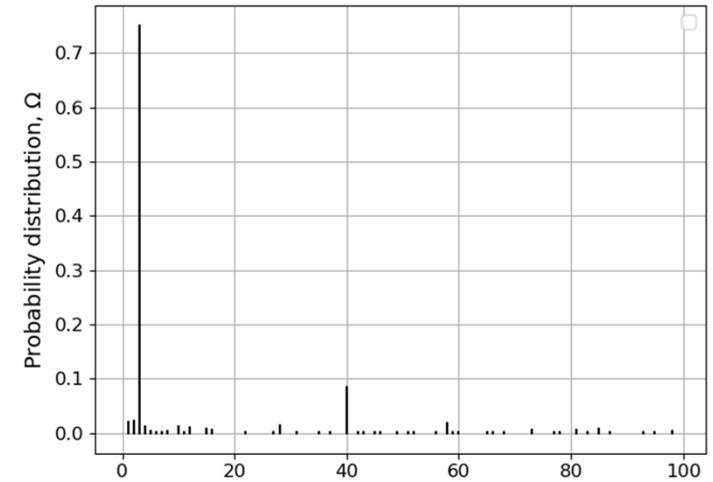
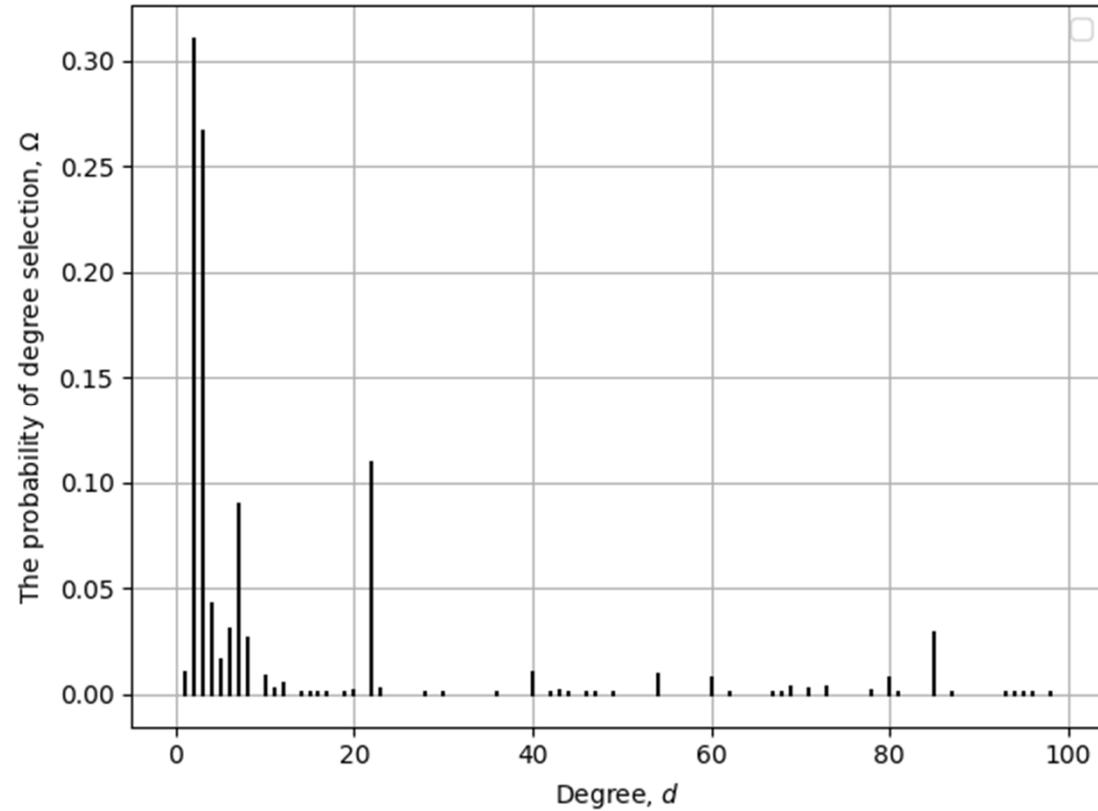
Refined Degree Distributions

Metaheuristic optimization



Chen et al. *Practical Optimization Framework for the Degree Distribution in LT Codes*

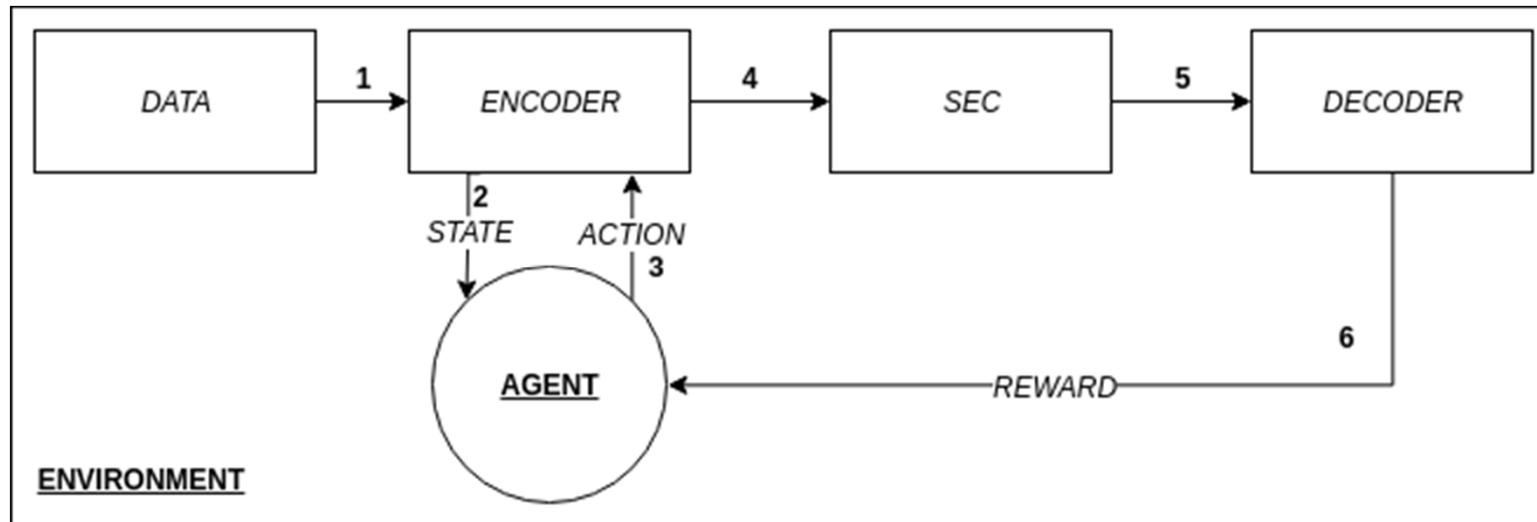
Refined Degree Distributions (OURS)



**Ω can be derived for any number of source symbols k
since we use neural networks as approximators**

Conceptual Scheme

(Optimization based on deep reinforcement learning)



- **Agent** encapsulates **Critic** and **Actor**
- Deep neural networks are used to approximate **Critic** and **Actor**
- Actor's policy is a stochastic policy and **the degree distribution Ω**
- The action space is discrete, and the policy is a categorical distribution
- The state space is a set of all possible combinations of the number of source symbols **k** and the expected reception overhead **Θ** .

Reward Definition

(For LT codes with Inactivation decoding)

The reward definition can be different for other LT-based codes

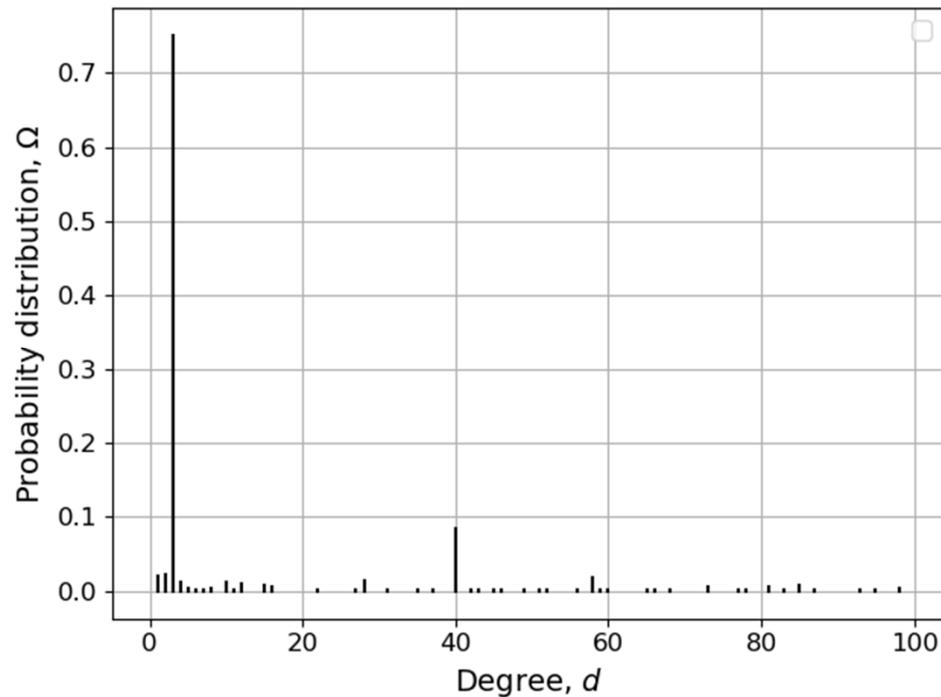
The reward distinguishes 3 decoding outcomes:

- The decoding failure: reward is in the range **[-1 ... 0)**
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- The decoding success (decoded by BP and/or GE): **[0 ... 1)**
-
- The decoding success (decoded only by BP): **the reward is 1**

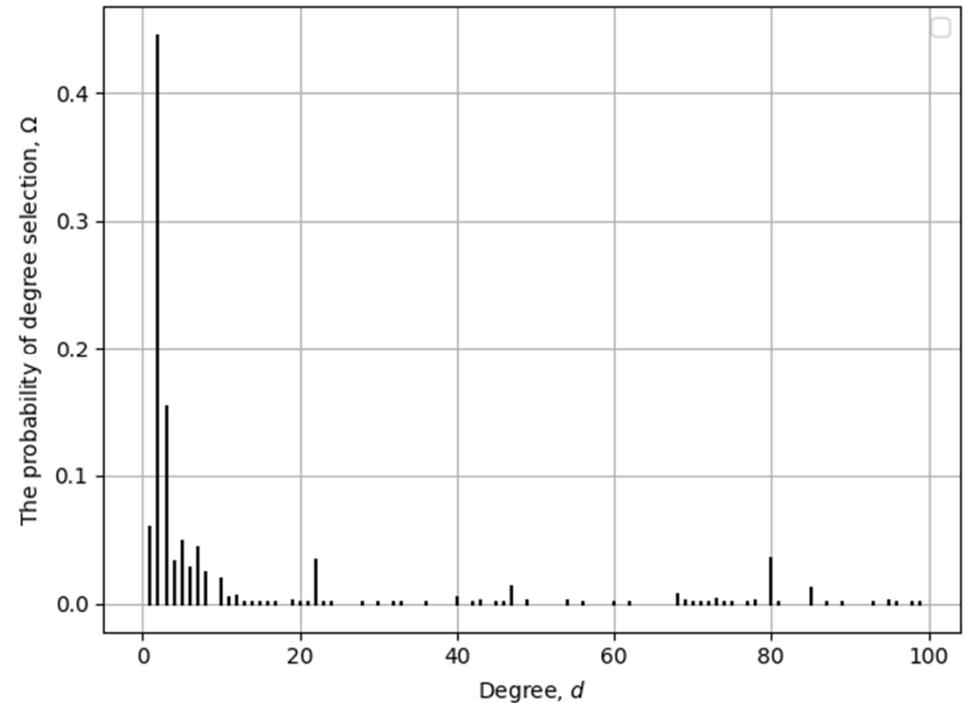
Expected reception overhead (1)

trade-off between decoding efficiency and runtime complexity

The degree distribution can be dynamically refined to trade-off runtime complexity over decoding inefficiencies and vice-versa.



$\Omega(k=150, \Theta=0)$

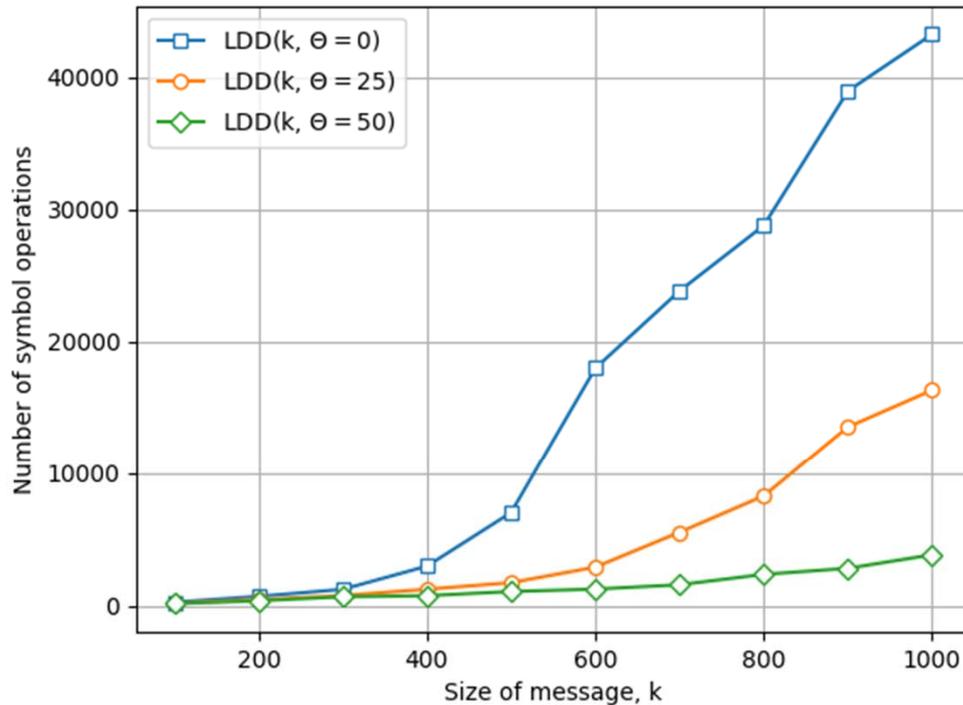


$\Omega(k=150, \Theta=50)$

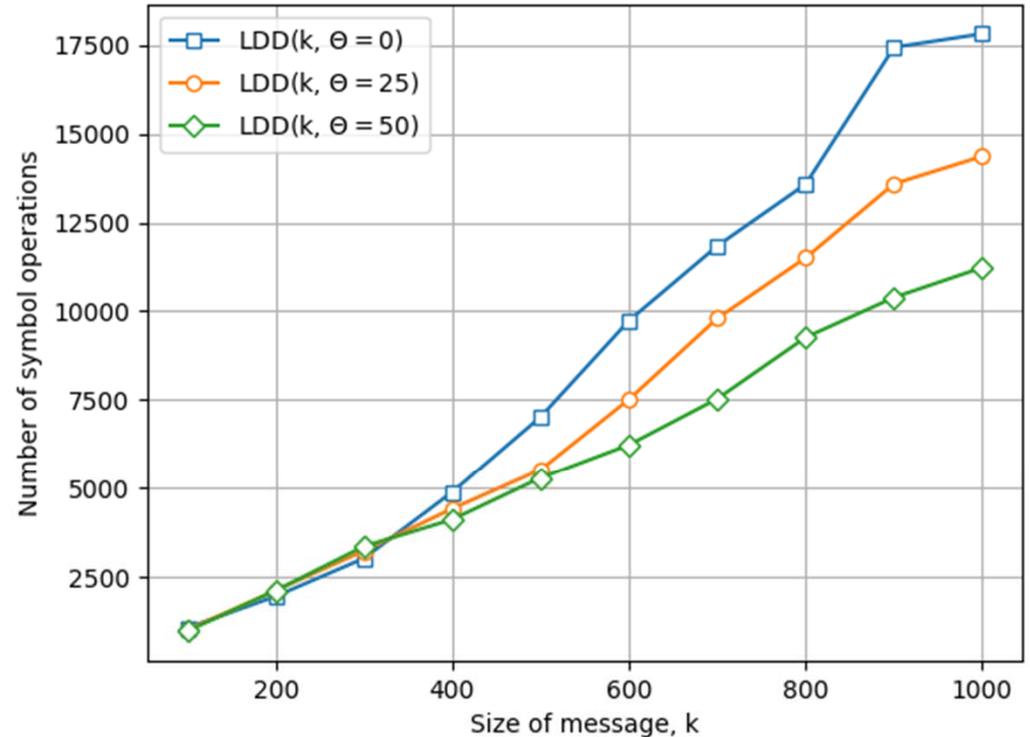
Expected reception overhead (2)

trade-off between decoding efficiency and runtime complexity

The bigger expected reception overhead the less iterations required to encode/decode the source data (the actual reception overhead is kept the same)



Decoding run-time complexity



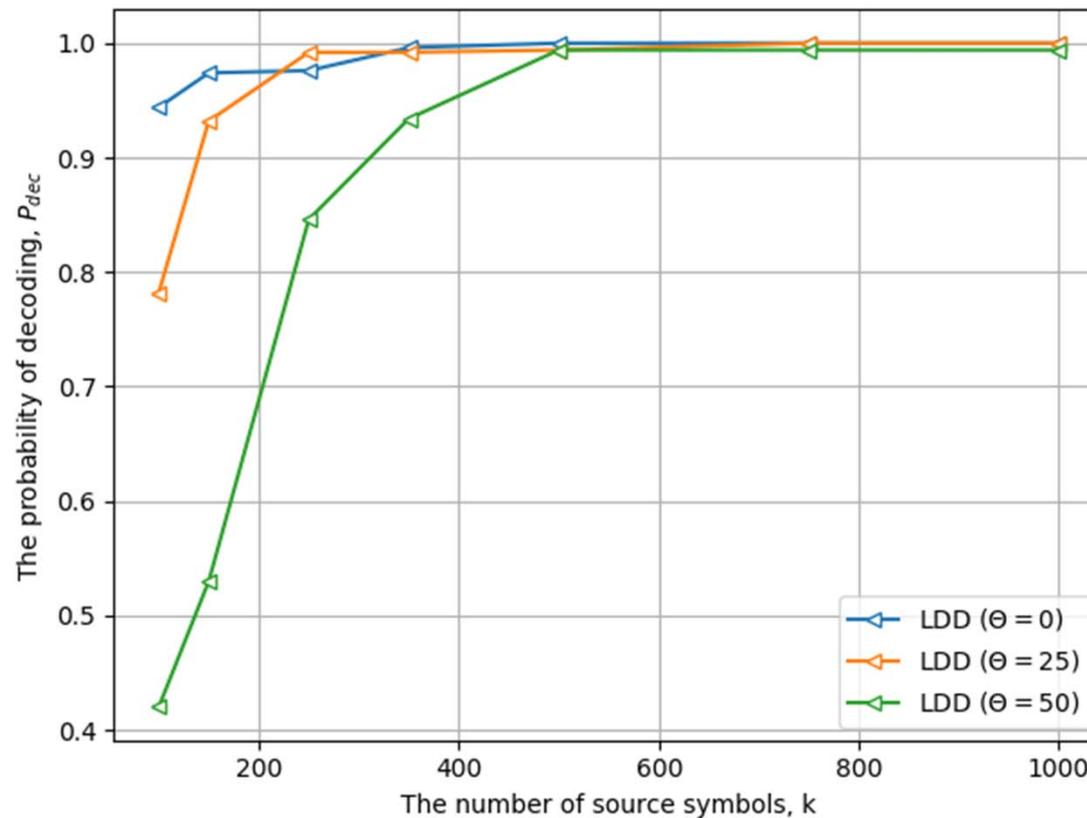
Encoding run-time complexity

The parameter θ of the LDD is used to control the probability of decoding and the encoding/decoding complexities

Expected reception overhead (3)

trade-off between decoding efficiency and runtime complexity

The bigger expected reception overhead the less iterations required to encode/decode the source data (the actual reception overhead is kept the same)



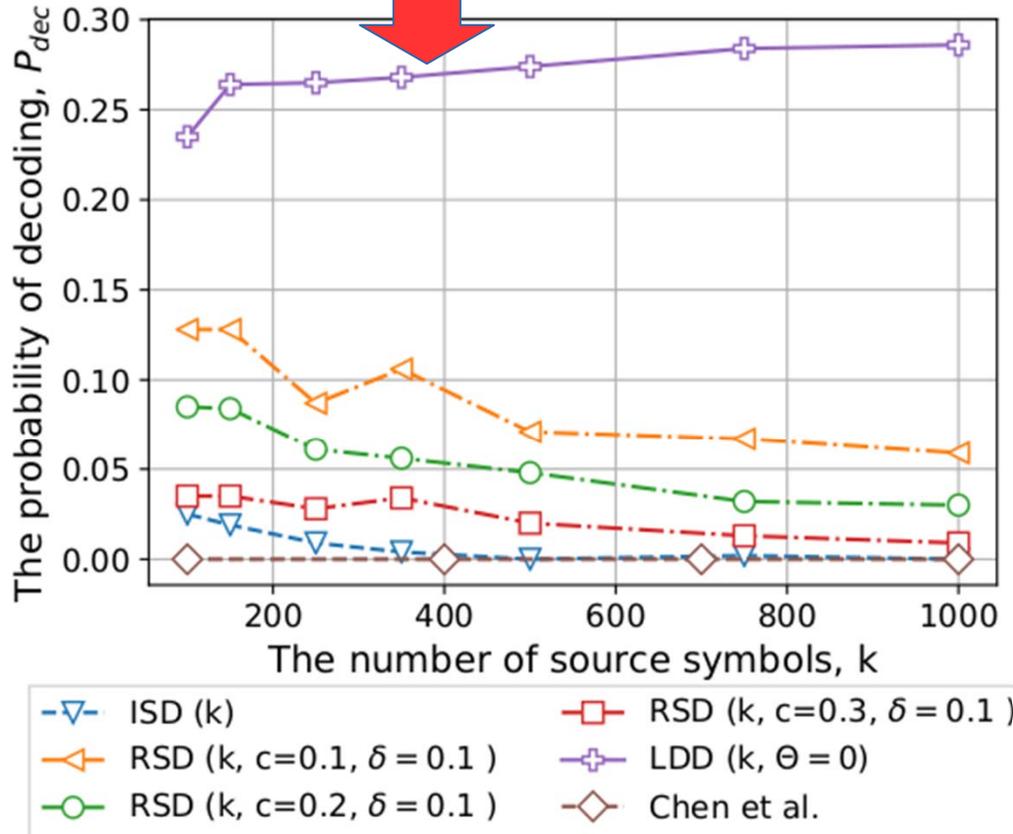
Decoding efficiency

The lower Theta values lead to the increased probability of decoding and worse encoding/decoding complexities, otherwise higher Theta leads to the opposite results. The experiments were averaged over 1000 independent runs for each k

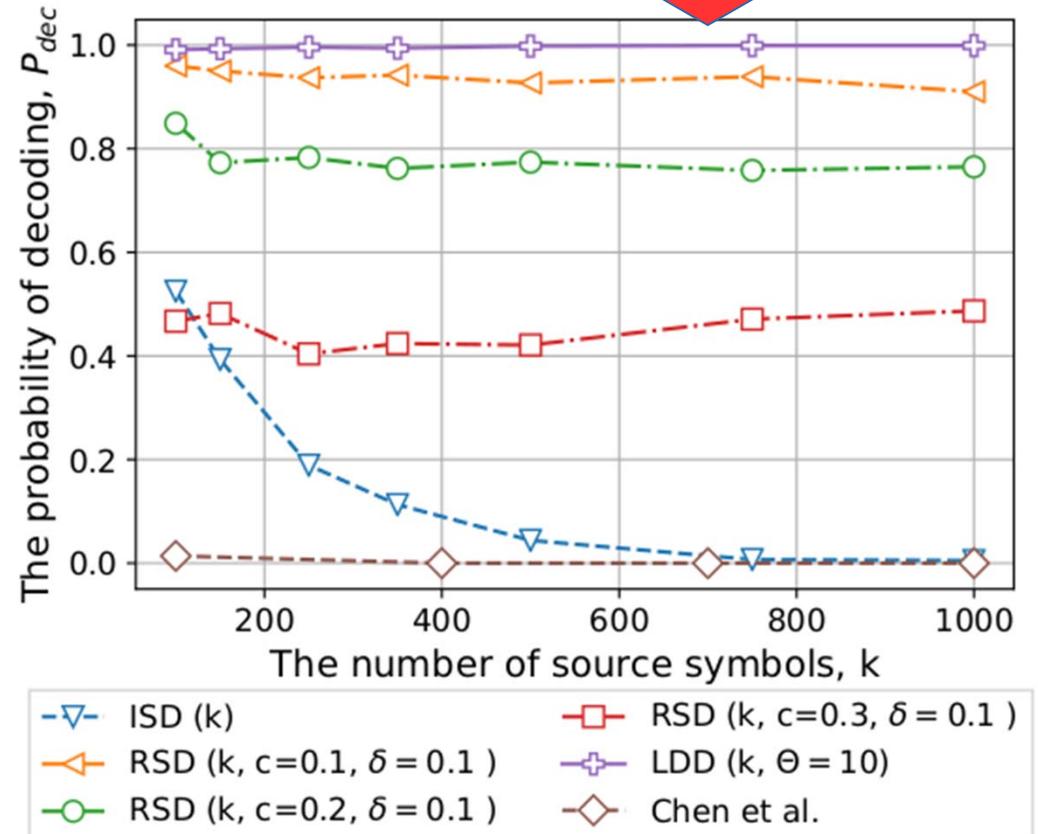
Evaluation (1)

decoding efficiency

We compared the codes with the LDD to the codes with the classical ISD, RSD, and the distributions proposed by Chen et al.



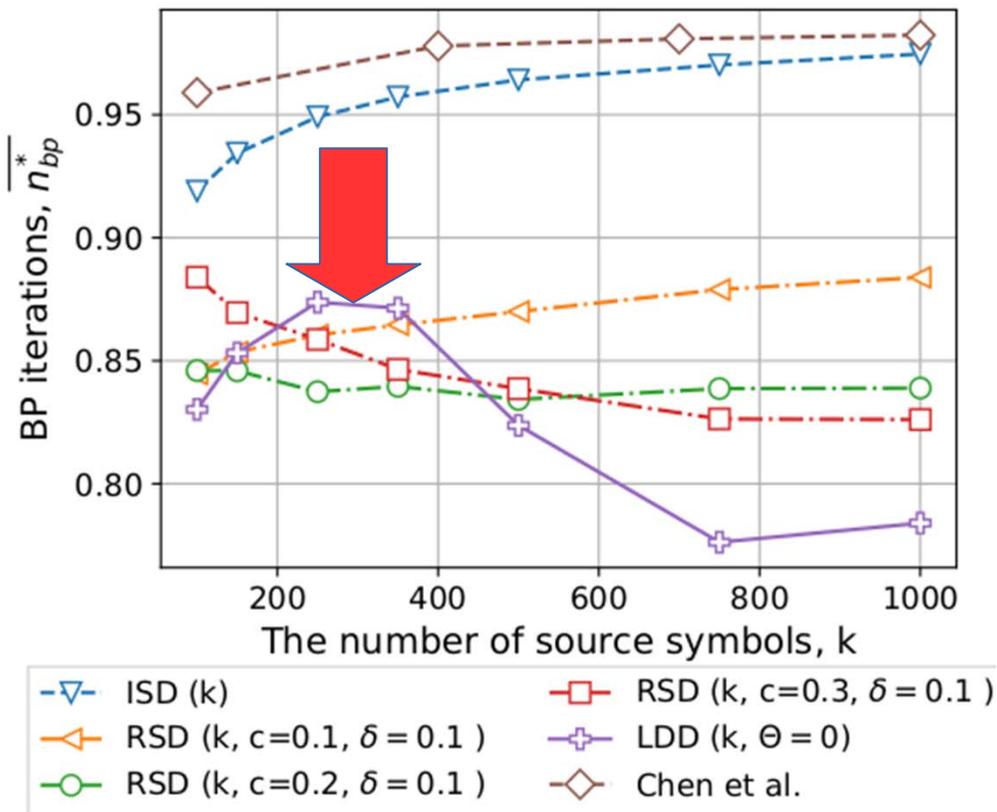
Reception overhead, $\sigma^* = 0$



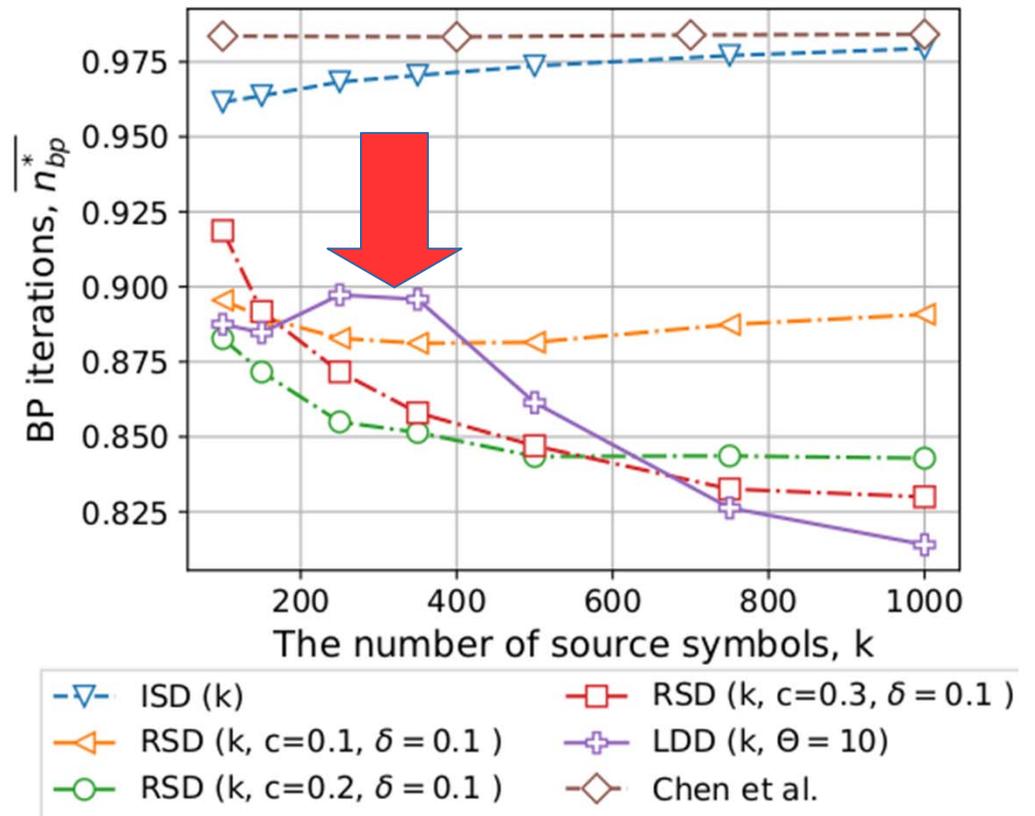
Reception overhead, $\sigma^* = 10$

Evaluation (2)

decoding run-time complexity



Reception overhead, $\sigma^* = 0$

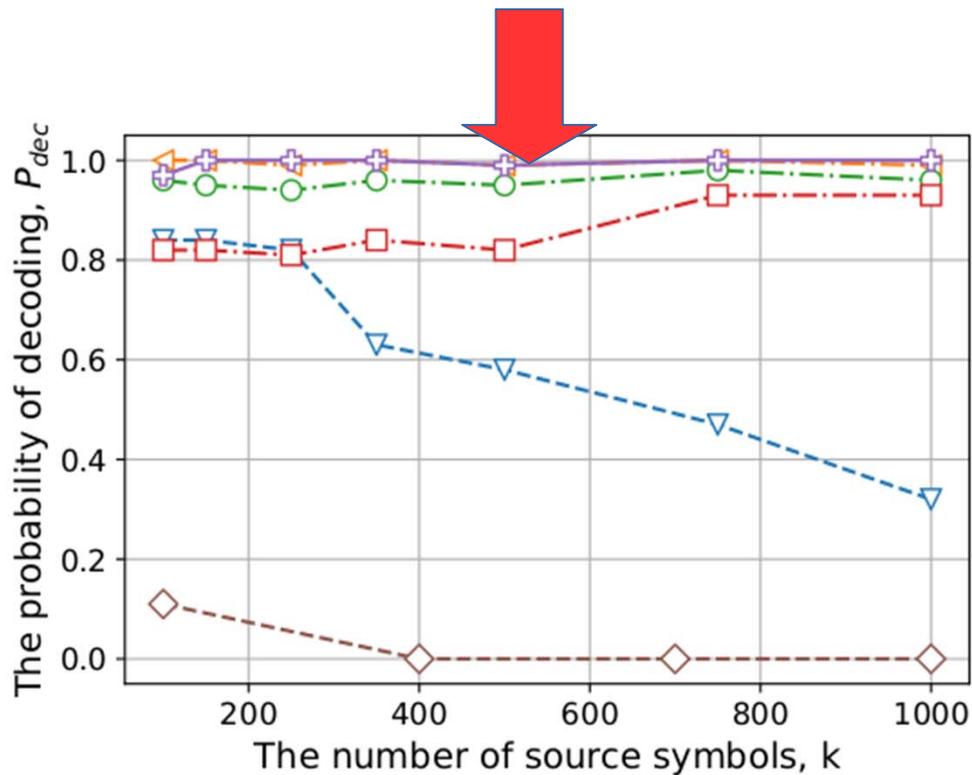


Reception overhead, $\sigma^* = 10$

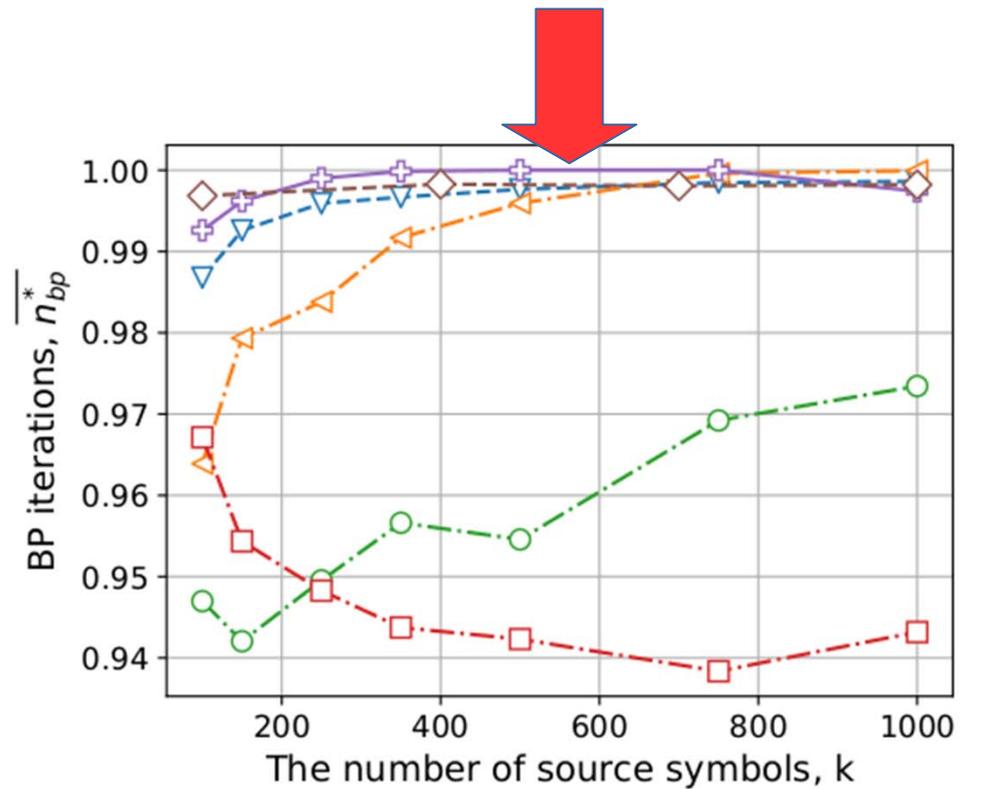
Evaluation (3)

decoding run-time complexity

Better decoding runtime complexity can be achieved by trading-off decoding efficiency and vice-versa



Decoding efficiency



Decoding run-time complexity

Concluding remarks

Why deep reinforcement learning after all ?

- The reinforcement learning in this paper doesn't have dimension explosion problems and can be easily used to obtain optimal degree distributions.
-
- The reinforcement learning can approximate a set of degree distributions for particular block lengths k and expected overheads Θ .
-
- Reduced time of optimization by means of the ability of neural networks to generalize is another beneficial property of the algorithm, e.g., if one uses evolutionary algorithms for optimization, then it is needed to perform optimization for each possible case separately.
-
- This optimization method is not only limited to the specific case presented here. The method can be used for any fountain codes derived from LT codes which utilize degree distributions for encoding procedures.
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Thank YOU for your time ! Any
Questions ?

