

Communicating Short Messages with and without feedback

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These slides are provided in the original PowerPoint for review and further study by attendees at the 2026 IEEE North American School of Information Theory.

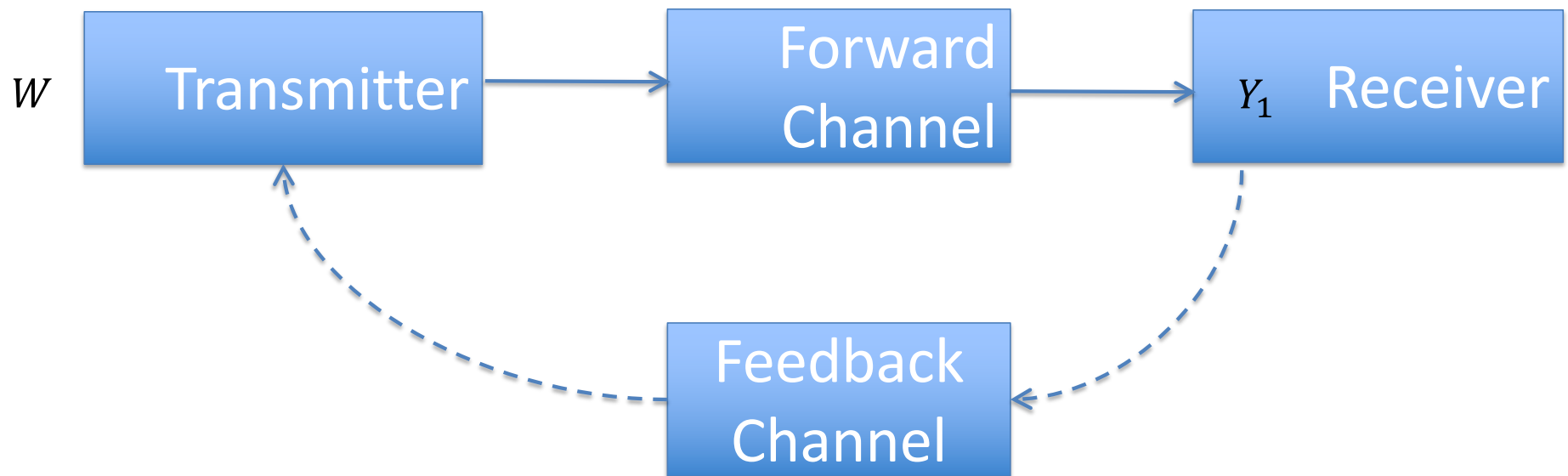
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Engineer Change.

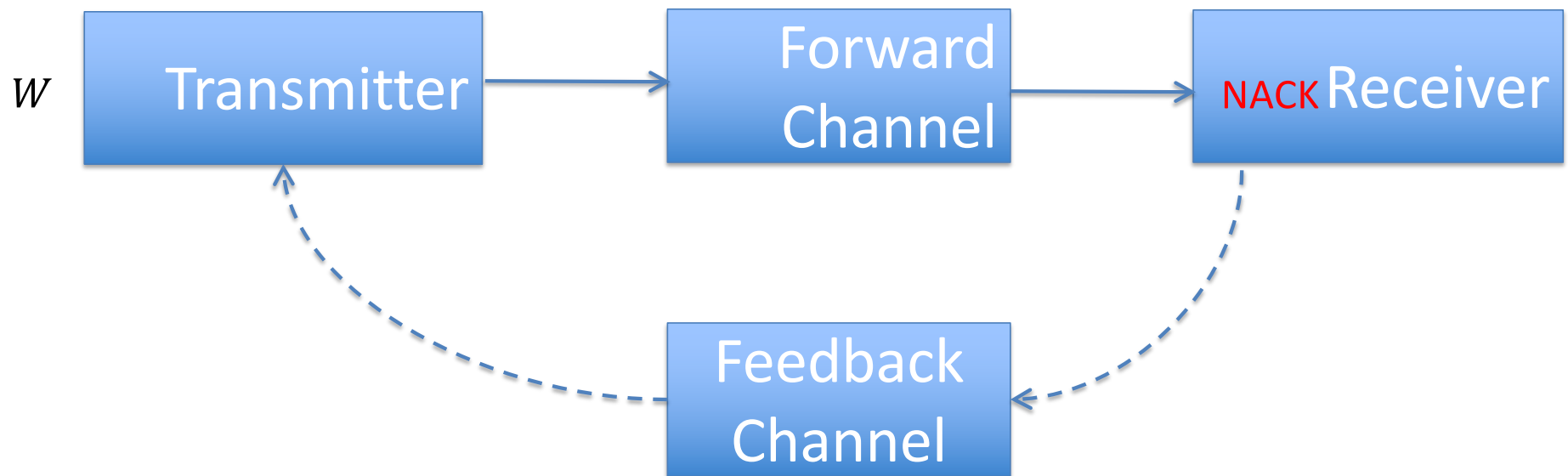
Communicating Short Messages with Feedback

- Feedback does not increase capacity, *but*
- For short messages, it *can* increase the rate
- Two main ways to use feedback
 1. Stop Feedback - that only decides when to stop transmission
 2. Full Feedback - that helps determine each transmitted symbol

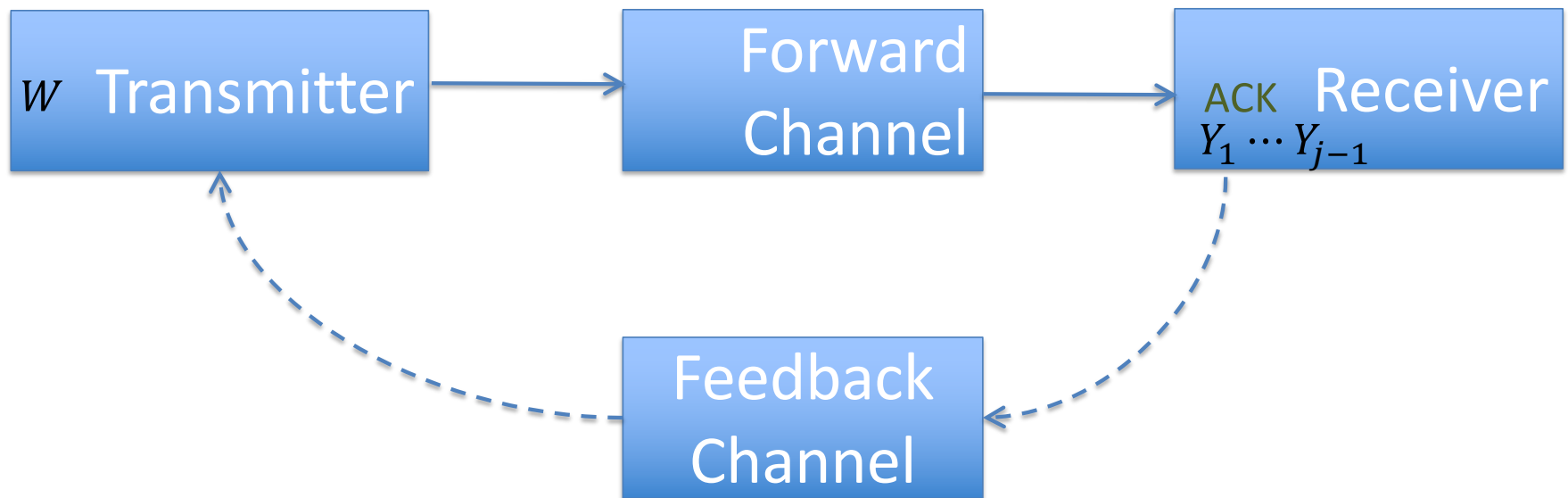
Full Feedback System Model



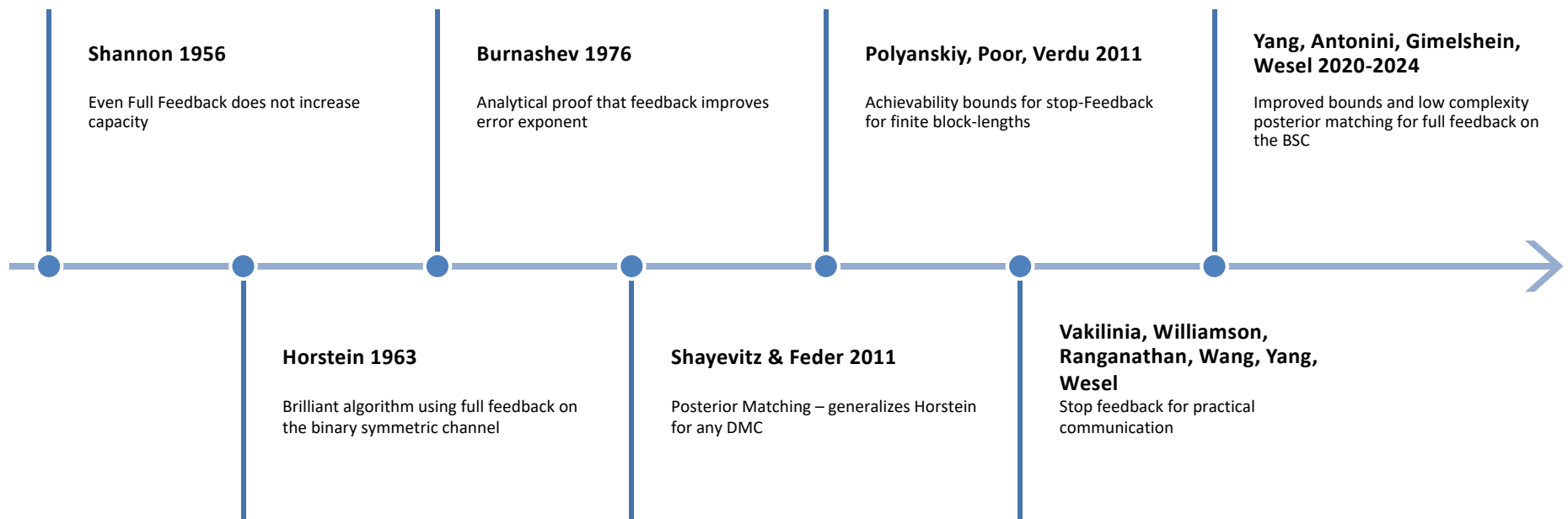
Stop Feedback System Model



Stop Feedback System Model



Feedback Timeline



Communicating Short Messages

A Play in Three Acts

1. Feedback does not increase capacity
2. Stop feedback increases the rate of short messages that achieve a target reliability
3. Full feedback further increases the rate of short messages that achieve a target reliability

Act 1:

Feedback does not increase capacity.



Even Full Feedback does not increase capacity

THE ZERO ERROR CAPACITY OF A NOISY CHANNEL
 Claude E. Shannon
 Bell Telephone Laboratories, Murray Hill, New Jersey
 Massachusetts Institute of Technology, Cambridge, Mass.

Abstract
 The zero error capacity C_0 of a noisy channel is defined as the least upper bound of rates at which it is possible to transmit information with zero probability of error. Various properties of C_0 are studied; upper and lower bounds and methods of evaluation of C_0 are given. Inequalities are obtained for the C_0 relating to the "sum" and "product" of two given channels. The analogous problem of zero error capacity C_0 for a channel with a feedback link is considered. It is shown that while the ordinary capacity of a memoryless channel without feedback, the zero error capacity may be greater. A solution is given to the problem of evaluating C_0 .

Introduction
 The ordinary capacity C of a noisy channel is defined as follows. There exists a rate R for the channel of increasing length n such that the probability of error approaches zero as n approaches infinity. For any rate R greater than C , it may

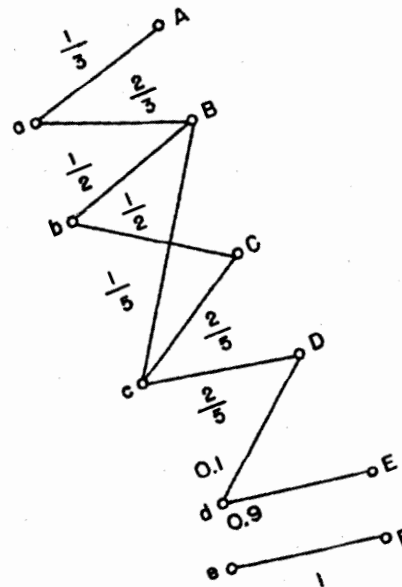
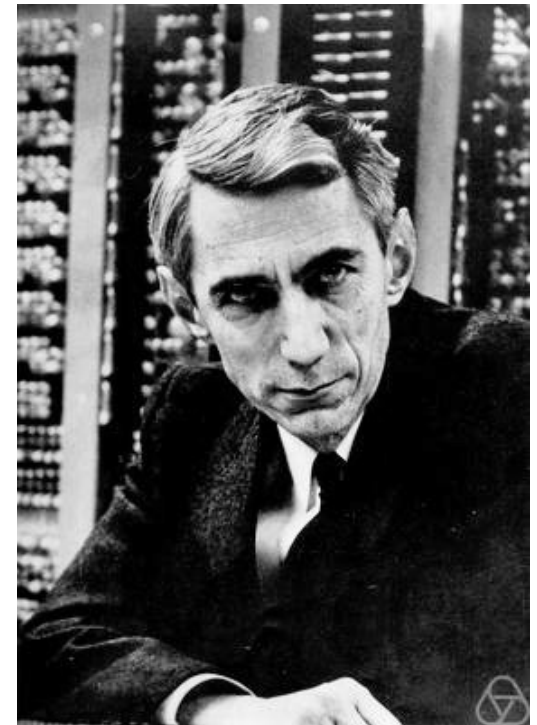


Fig. 1

take to be the integers $1, 2, \dots, M$ into a set of M input words of length n will be called a code of length n . $R = \frac{1}{n} \log M$ will be the rate for this code. Unless stated otherwise, $\log$ will mean such a logarithm as will mean natural (base e) or binary (base 2) units.



Shannon

http://owpodb.mfo.de/detail?photo_id=3807, CC BY-SA
[mons.wikimedia.org/w/index.php?curid=45380422](https://commons.wikimedia.org/w/index.php?curid=45380422)

Consider the gain in mutual information ΔI from transmitting $X_j = f(W, Y_1 \cdots Y_{j-1})$.



feedBack: $B = Y_1 \cdots Y_{j-1}$

Mutual information between message W and receiver's knowledge

Before we send $X_j = f(W, Y_1 \cdots Y_{j-1})$: $I(W; B)$

After we send $X_j = f(W, Y_1 \cdots Y_{j-1})$: $I(W; B, Y_j)$

$$\Delta I = I(W; B, Y_j) - I(W; B)$$

It turns out that ΔI cannot exceed C

$$\Delta I = \sum_b P_B(b) \Delta I(b)$$

For each possible feedback b , $\Delta I(b) \leq C$.



Act 2:

Stop feedback increases the rate of short messages that achieve a target reliability

“Stop” Feedback for Short Messages



Polyanskiy



Poor



Verdu

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<https://commons.wikimedia.org/w/index.php?curid=34583438>

An information density analysis that bit
on their earlier work.

Information Density i

- Information density i is The stochastic symbol-wise random variable whose expectation is the mutual information.
- Computed *per possible codeword* using a received symbol y_j and the corresponding symbol $\hat{x}_j$ from a potential codeword.

$$i(y_j, \hat{x}_j) = \log_2 \frac{f_{Y|X}(y_j|\hat{x}_j)}{f_Y(y_j)} \quad (21)$$

Information Density

- Computed using a received symbol y_j and the corresponding symbol $\hat{x}_j$ from a potential codeword.

$$i(y_j, \hat{x}_j) = \log_2 \frac{f_{Y|X}(y_j|\hat{x}_j)}{f_Y(y_j)} \quad (21)$$

- Accumulated information density (AID) adds up these symbol-wise terms.

$$i(y^n, \hat{x}^n) = \sum_{j=1}^n \log_2 \frac{f_{Y|X}(y_j|\hat{x}_j)}{f_Y(y_j)} \quad (22)$$

Accumulated Information Density and $I(X; Y)$

$$i(y^n, \hat{x}^n) = \sum_{j=1}^n \log_2 \frac{f_{Y|X}(y_j | \hat{x}_j)}{f_Y(y_j)} \quad (22)$$

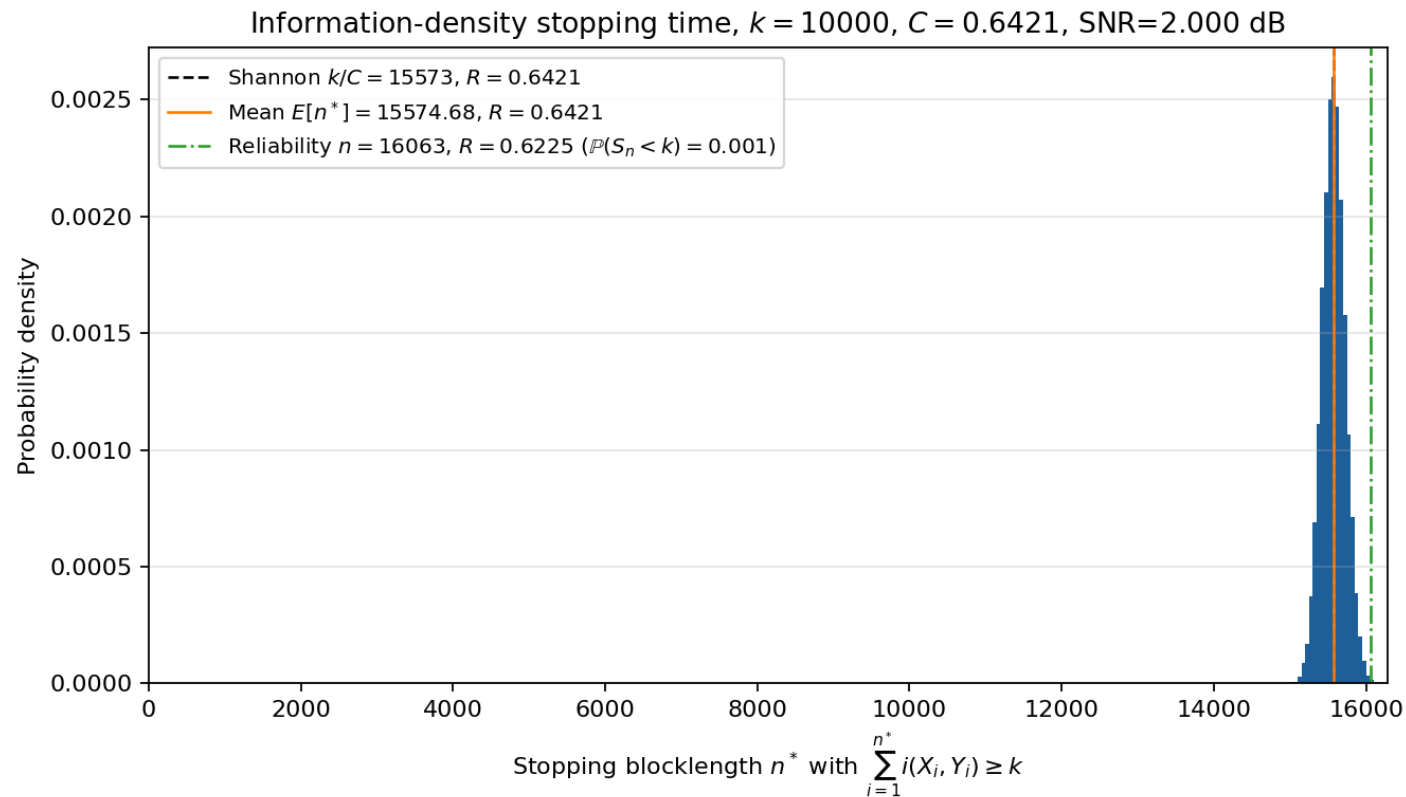
The Information Density Stopping Rule

- The receiver decides to terminate decoding when the accumulated information density for one of the possible codewords is above γ .
- Reasonable values of γ are on the order of the number of bits k in the message.
- Increasing γ lowers the probability of error but also increases the stopping time.

$$\tau = \inf\{n \geq 0 : \imath(X^n; Y^n) \geq \gamma\} \quad (25)$$

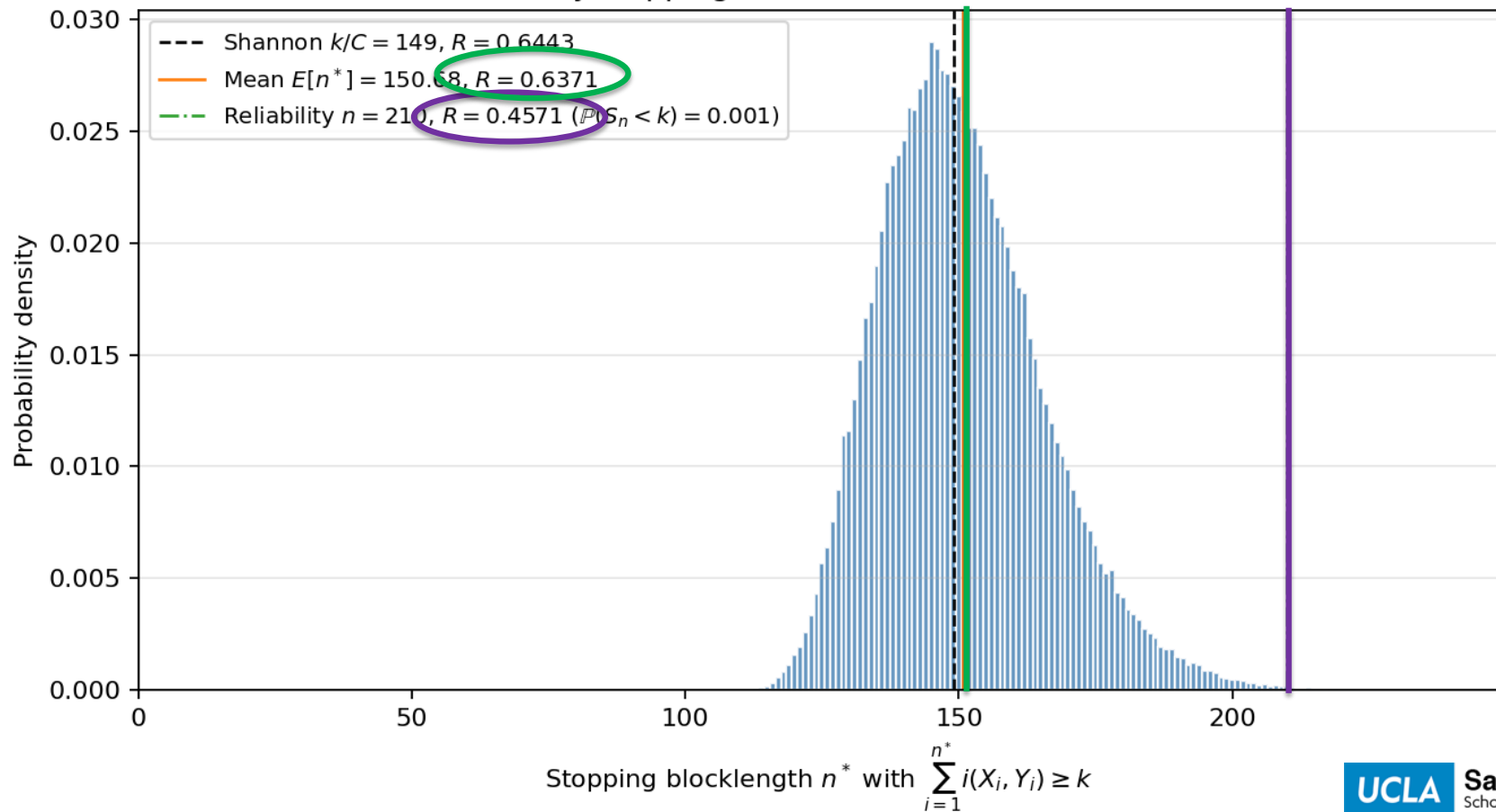
$$\bar{\tau} = \inf\{n \geq 0 : \imath(\bar{X}^n; Y^n) \geq \gamma\}. \quad (26)$$

Block-length n^* where $i \geq k$: $k=10,000$ bits

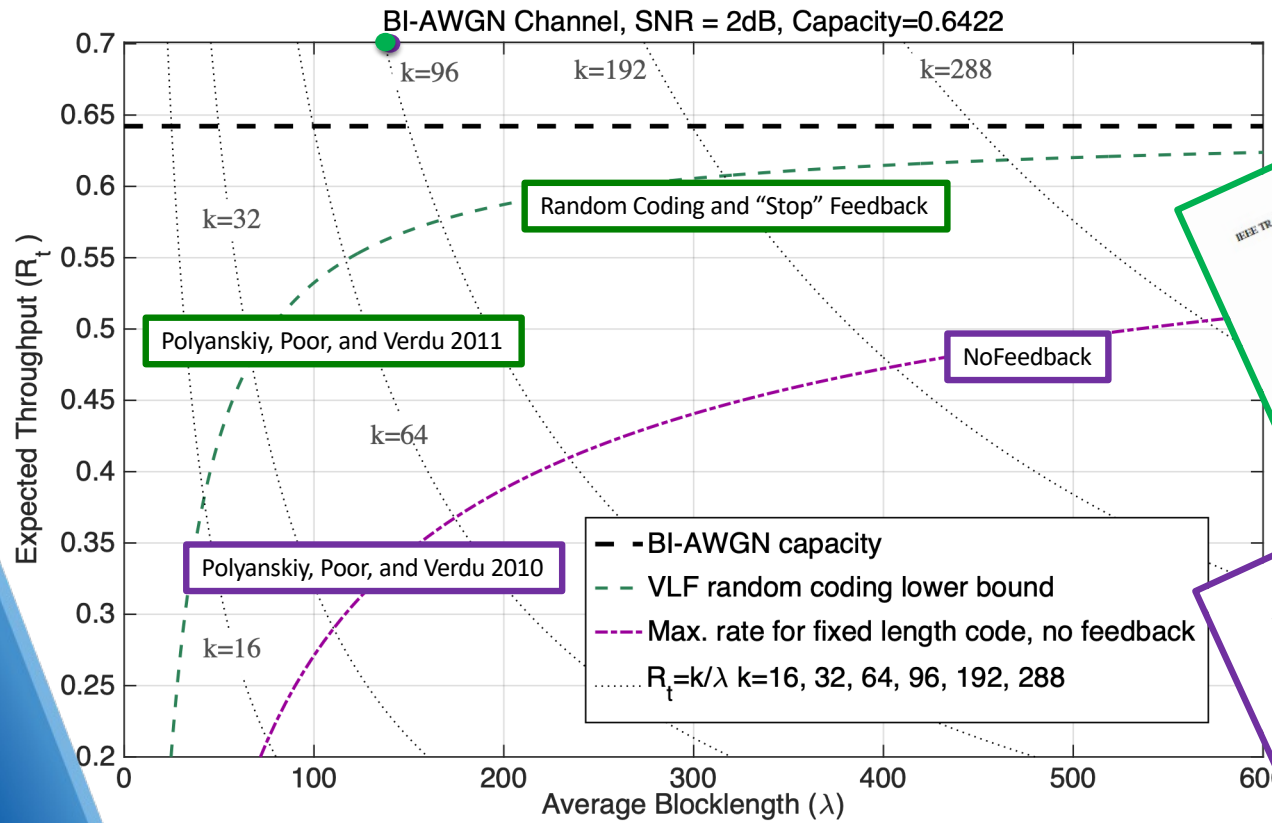


Block-length n^* where $i \geq k$: $k=96$ bits

Information-density stopping time, $k = 96$, $C = 0.6421$, SNR=2.000 dB



Polyanskiy, Poor, Verdu Achievable Rates



IEEE TRANSACTIONS ON INFORMATION THEORY, VOL. 57, NO. 8, AUGUST 2011

Feedback in the Non-Asymptotic Regime

Yury Polyanskiy, Member, IEEE, H. Vincent Poor, Fellow, IEEE, and Sergio Verdú, Fellow, IEEE

Abstract—Without feedback, the backoff from capacity due to non-asymptotic blocklength can be quite substantial for blocklengths and error probabilities of interest in many practical applications. In this paper, novel achievability bounds are used to demonstrate that in the non-asymptotic regime, the maximal achievable rate improves dramatically thanks to variable-length coding and feedback. For example, for the binary symmetric channel with capacity $1/2$, the blocklength required to achieve 90% of the best fixed-blocklength code (even with noiseless feedback) is virtually all the advantages of noiseless feedback.

Index Terms—Achievability, channel capacity, coding for noisy channels, converse, finite blocklength regime, Shannon theory.

channel capacity is the largest rate at which information can be transmitted regardless of the desired error probability, provided that the blocklength is allowed to grow without bound. In practice, it is of vital interest to assess the backoff from capacity required to sustain the desired error probability for a given fixed finite blocklength. Unfortunately, no guidance is offered either by the reliability function, which answers the question, or by the exponential decay of error probability in the nonasymptotic regime, there are no exact asymptotic bounds which bound the error probability. In this paper, we show several tight approximations for the backoff from capacity for blocklengths as short as 100. To this end, we also show the channel dispersion V , which is the variability of the channel relative to a Gaussian channel with the same capacity. Specifically, the rate is approximated by

$$\frac{1}{n} \log M^*(n, \epsilon) \approx \frac{1}{n} \log M^*(n, \epsilon) - \frac{V}{2n} \log \frac{1}{1 - \epsilon}$$

where $M^*(n, \epsilon)$ is the maximal achievable rate for blocklength n and error probability ϵ .

Channel Coding Rate in the Finite Blocklength Regime

Yury Polyanskiy, Student Member, IEEE, H. Vincent Poor, Fellow, IEEE, and Sergio Verdú, Fellow, IEEE

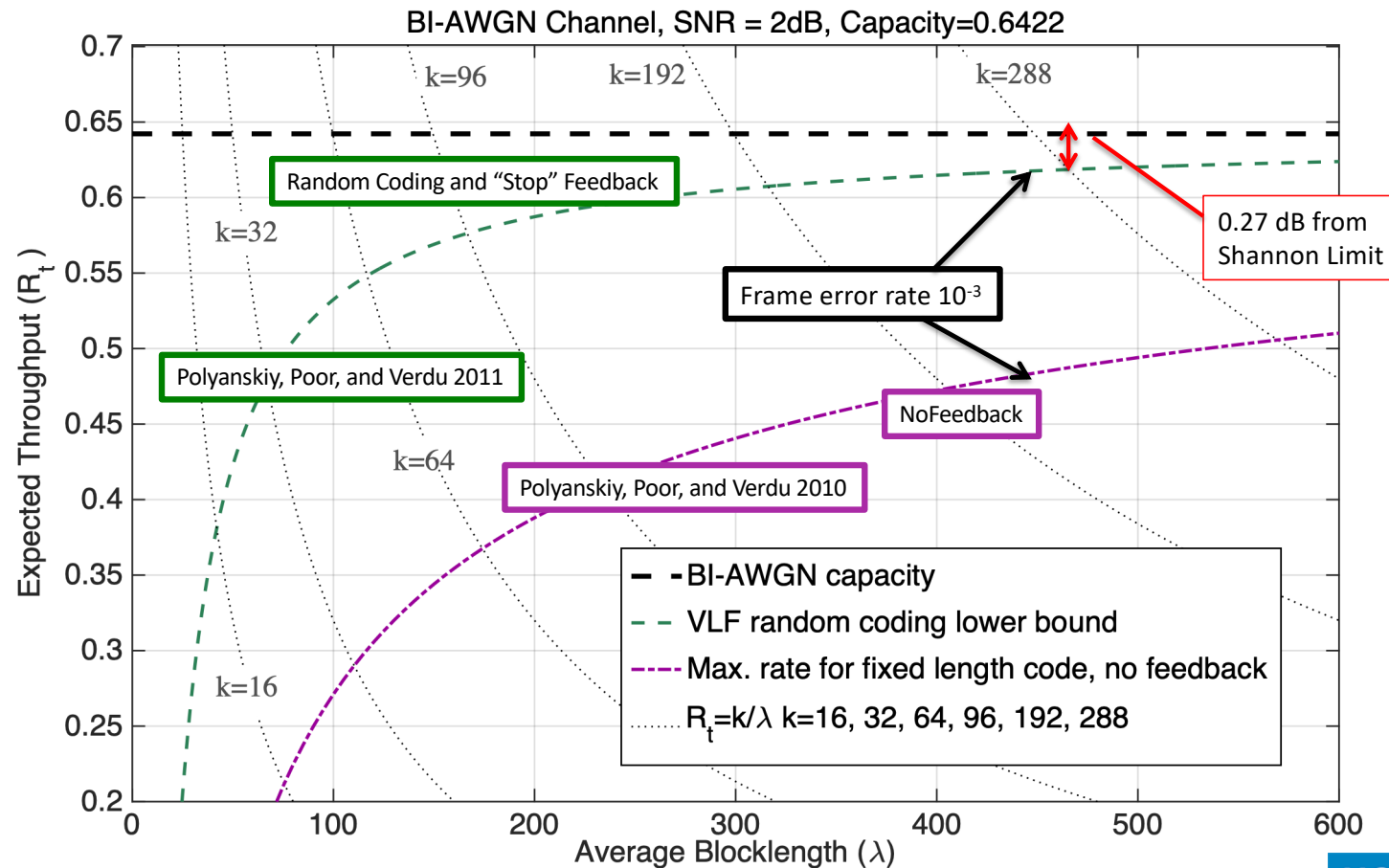
Abstract—This paper investigates the maximal channel coding rate achievable at a given blocklength and error probability. For general classes of channels new achievability and converse bounds are given, which are tighter than existing bounds for wide ranges of parameters of interest, and lead to tight approximations of the maximal achievable rate for blocklengths n as short as 100. It is also shown analytically that the maximal rate achievable with error probability ϵ is closely approximated by $C - \sqrt{\frac{V}{n}} Q^{-1}(\epsilon)$ where C is the capacity, V is a characteristic of the channel referred to as channel dispersion, and Q is the complementary Gaussian cumulative distribution function.

I. INTRODUCTION

The channel coding theorem involves three quantities: the size of any code with error probability ϵ , the rate of a code that can be achieved with length n and error probability ϵ , and the rate is approximated by

$$\frac{1}{n} \log M^*(n, \epsilon) \approx \frac{1}{n} \log M^*(n, \epsilon) - \frac{V}{2n} \log \frac{1}{1 - \epsilon}$$

A dramatic increase in rate at short blocklength



IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. 63, NO. 7, JULY 2015

IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. 64, NO. 6, JUNE 2016

Variable-Length Coding for Limited Blocklengths With Decoding Delay Constraints

Optimizing Transmission Lengths for Limited Blocklengths With Nonbinary LDPC Examples

Incremental

Optimizing Trans...

Feedback With Nonbilla...

2017 IEEE International Symposium on Information Theory (ISIT)

Approaching Capacity Using Incremental

Redundancy without Feedback

IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. 63, N...

Like LDPC Cod...

Approaching Capacity without Redundancy without

IEEE TRANSACTIONS ON COMMUNICATIONS

Protograph-Based Raptor-Like LDPC Codes

Future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIT.2019.2895322.

Transactions on Information Theory

Based Raptor-Like LDPC

Lengths

Fellow, IEEE,

Protograph-Based Raptor-Like LDPC

Quasi-Cyclic Protograph-Based Raptor-Like LDPC Codes for Short Block-Lengths

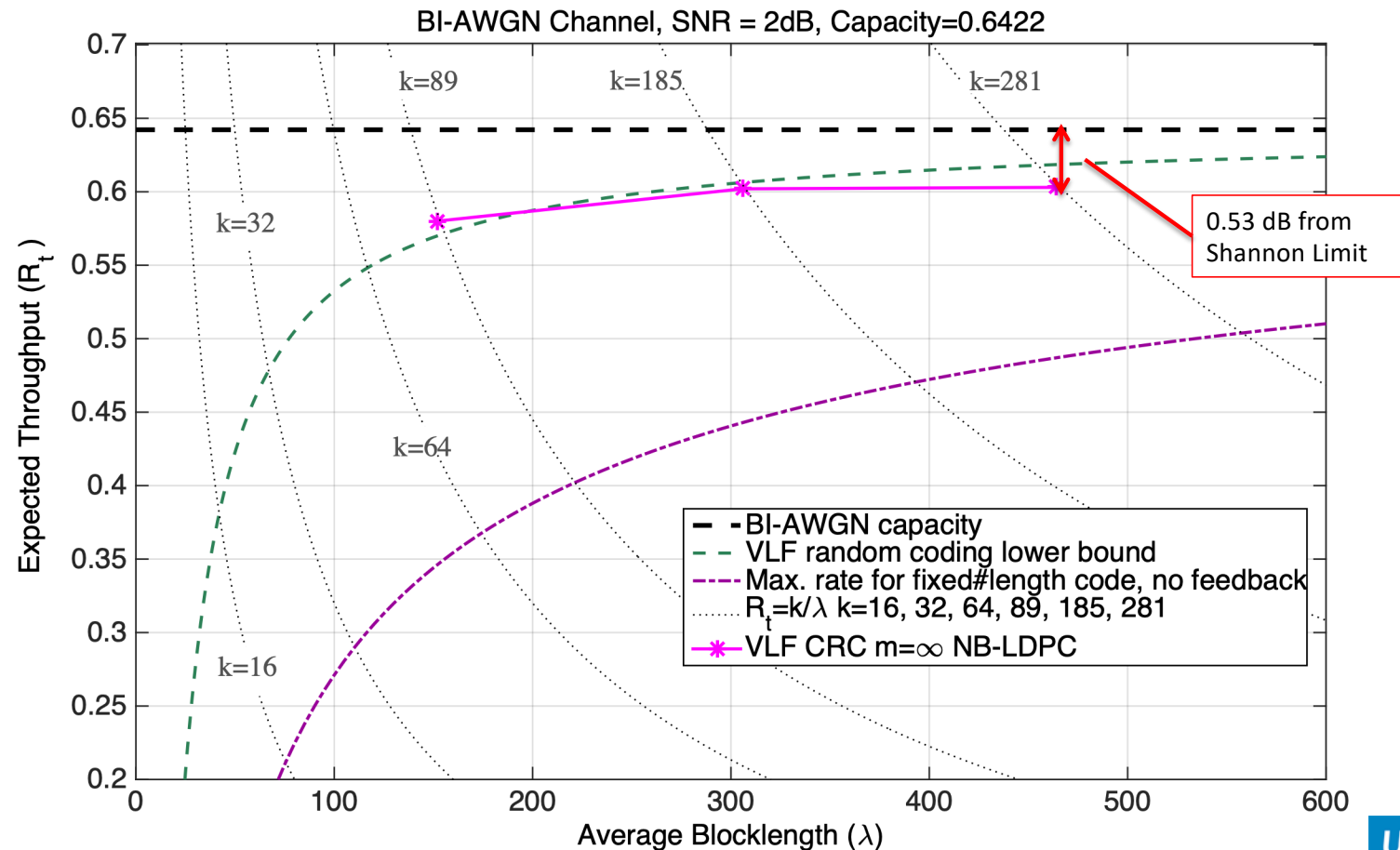
Ranganathan, Student Member, IEEE, Dariush Divsalar, Life Fellow, IEEE, and Richard D. Wesel, Senior Member, IEEE

Cyclic Protograph Codes for Short Block Lengths

Jagan V. S. Ranganathan, Student Member, IEEE, Dariush Divsalar, and Richard D. Wesel, Senior Member, IEEE

of a certain size over the channel. If the receiver is unable to decode the received noisy codeword, the transmitter transmits additional codeword symbols to the receiver to aid in decoding. The process continues until the received codeword can be decoded. The process has been called Chase Combining (CC) [1].

Limite Feedback, but more than Stop Feedback



Rate-Compatible Coding with Limited Feedback

Optimizing Transmission Lengths for Limited Feedback With Nonbinary LDPC Examples

Kasra Vakilineia, Student Member, IEEE, Sudarsan V. S. Ranganathan, Member, IEEE, Dariush Divsalar, Life Fellow, IEEE, and Richard D. Wesel, Senior Member, IEEE

Abstract—This paper presents a general approach for optimizing the number of symbols in increments (packets of incremental redundancy) in a feedback communication system with a limited number of increments. This approach is based on a tight normal approximation on the rate for successful decoding. Applying this approach to a variety of feedback systems using nonbinary (NB) low-density parity-check (LDPC) codes that achieve greater than 90% of capacity can be achieved with blocklengths fewer than 500 transmitted bits. One result shows that the performance with ten increments of increments is comparable to an infinite number of increments. The normal approximation demonstrates that the normal approximation with fading channels as well as larger QAM with feedback

paper is not exclusively for NB-LDPC codes, but NB-LDPC codes are used for demonstration because they perform well in the short-blocklength regime (150 to 600 bits) that is of interest.

In VLFT analysis of [2], the receiver provides full noiseless feedback to the transmitter. The transmitter sends additional incremental bits until it knows the receiver has decoded the message correctly, resulting in zero probability of error. The “T” in VLFT stands for termination and corresponds to a noiseless transmitter confirmation (NTC) bit that the transmitter uses to terminate the transmission. The NTC is transmitted through a channel different from the main communication channel. In contrast, VLF (without the “T”) does not have the advantage of an NTC. All VLF forward transmissions go over the same noisy channel. Thus, there is a nonzero probability of undetected error.

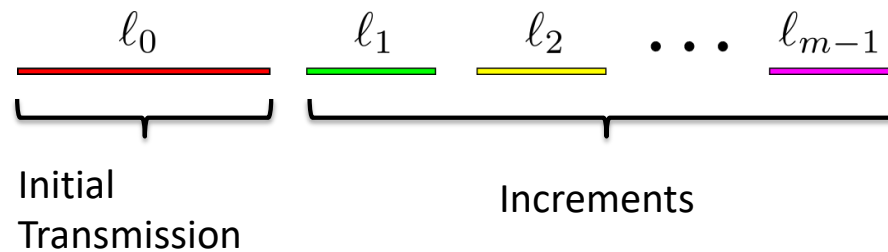
VLFT are examples of hybrid automatic repeat schemes. Prior to Polyanskiy et al. [2] and feedback schemes had been studied including for example [5]—including HARQ, discuss with ARQ, and shows



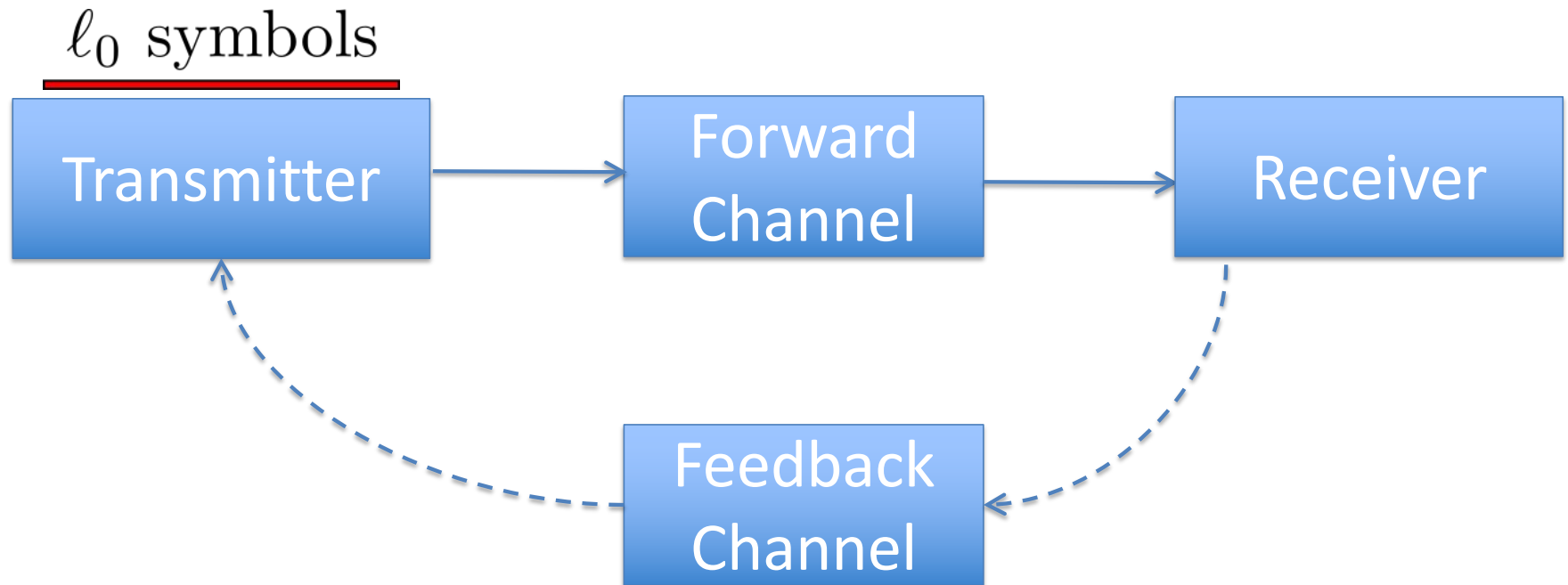
Vakilineia

A Rate-compatible Encoder

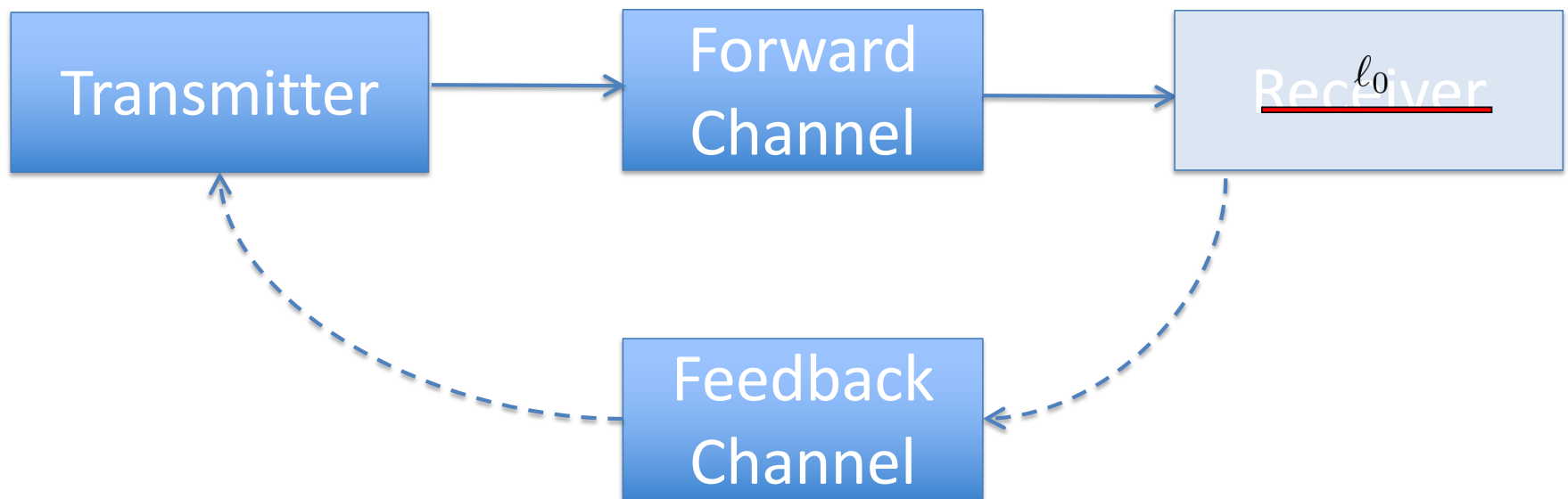
k bits of user information



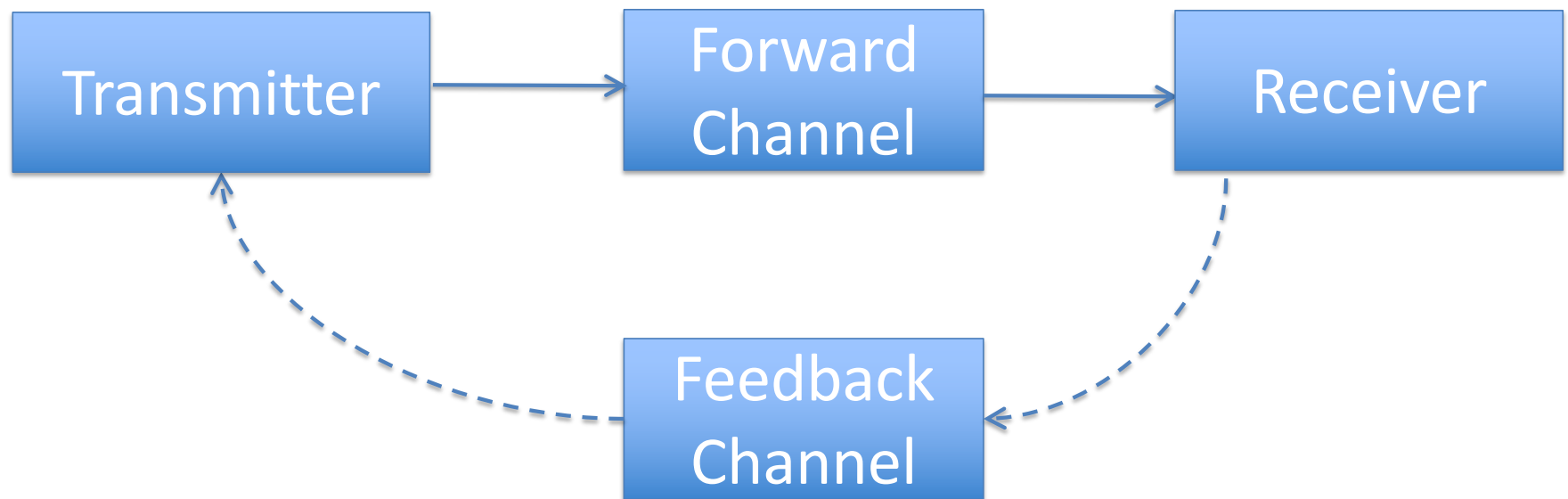
Incremental-Redundancy Hybrid ARQ



Incremental-Redundancy Hybrid ARQ



Incremental-Redundancy Hybrid ARQ

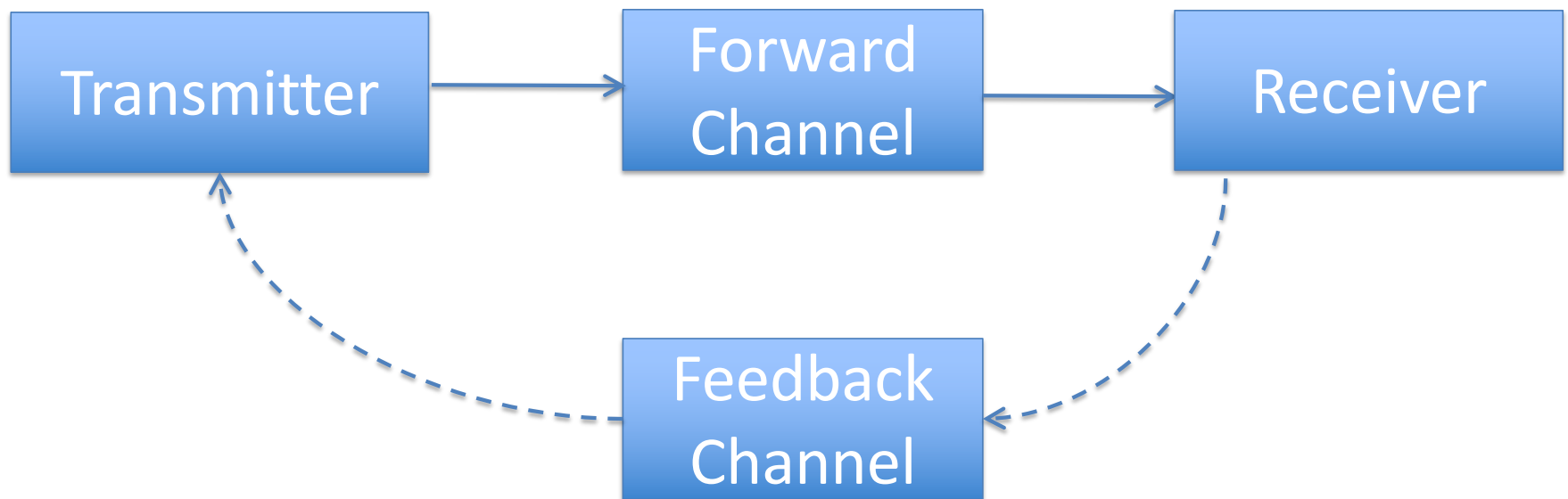


The probability that the decoder declares **success** is $P_{\text{ACK}}^{(\ell_1)}$.

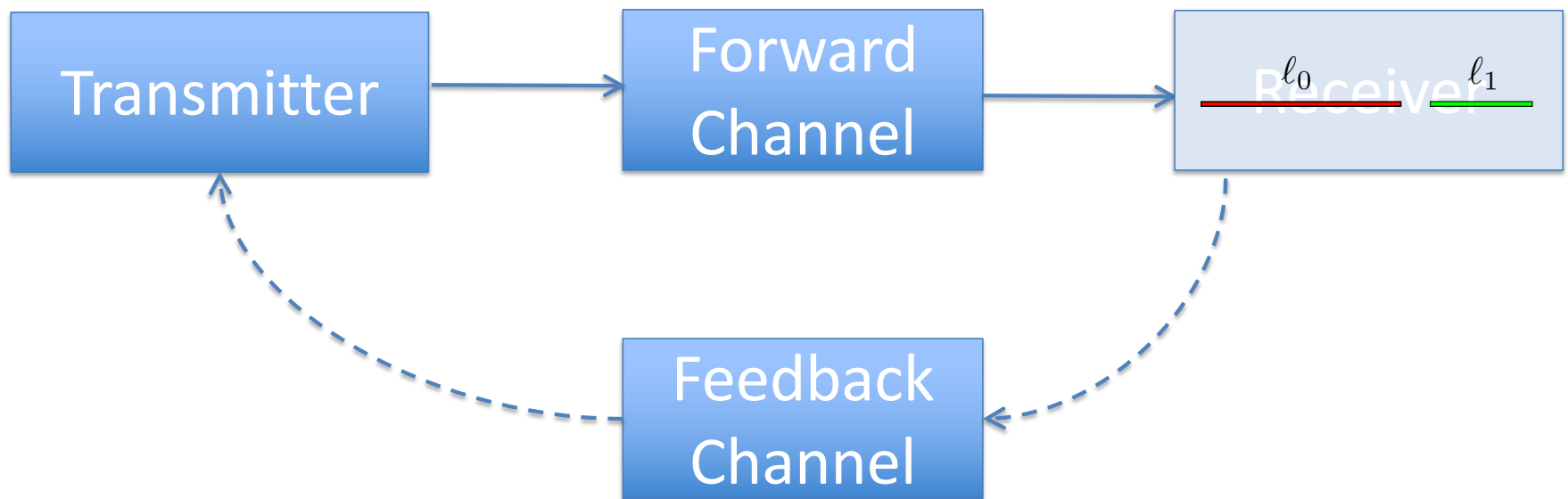
The probability that the decoder declares **failure** is $P_{\text{NACK}}^{(\ell_1)}$.

Incremental-Redundancy Hybrid ARQ

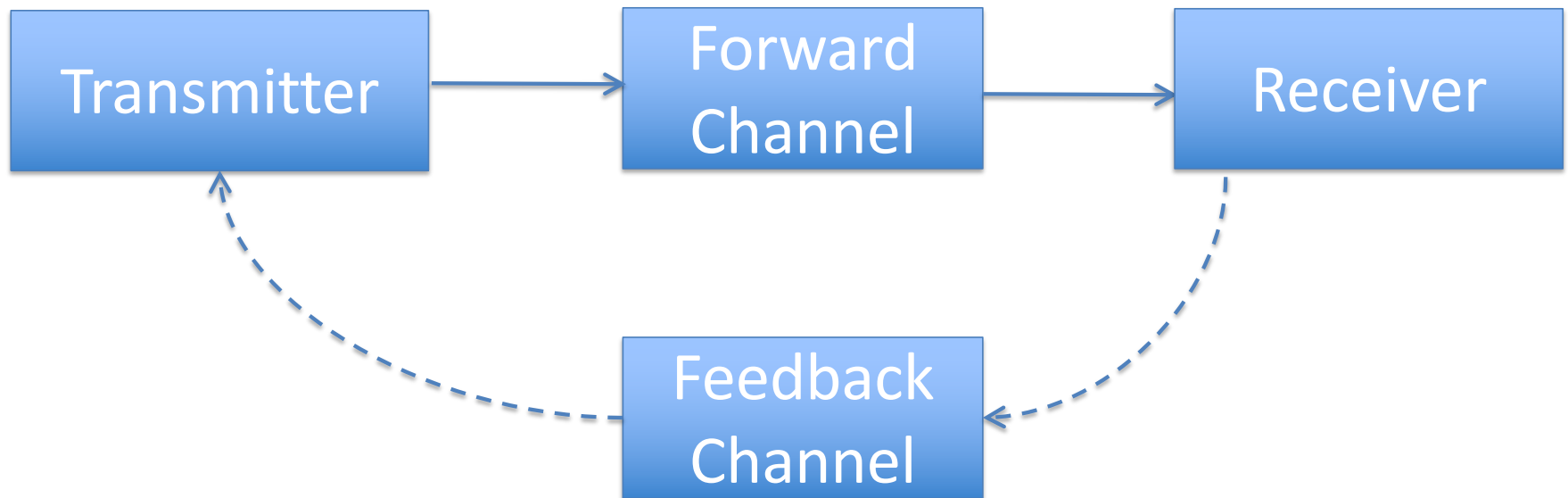
ℓ_1 symbols



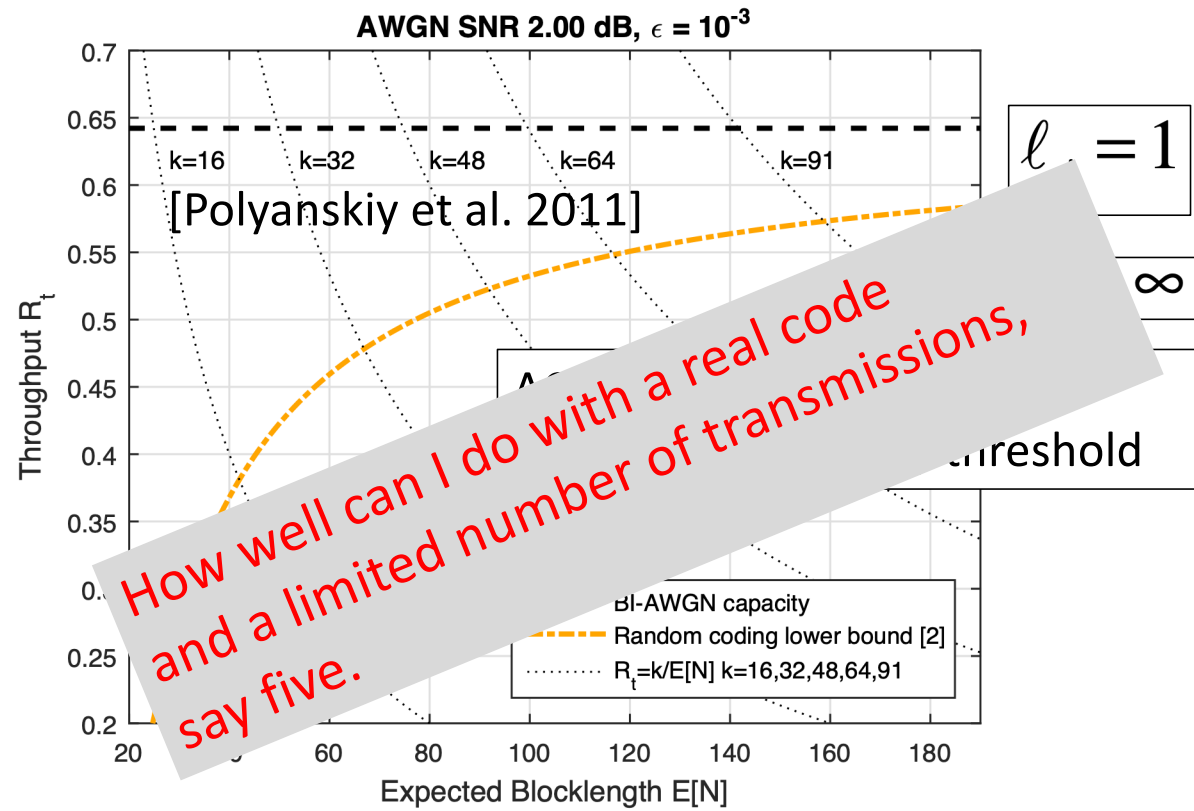
Incremental-Redundancy Hybrid ARQ



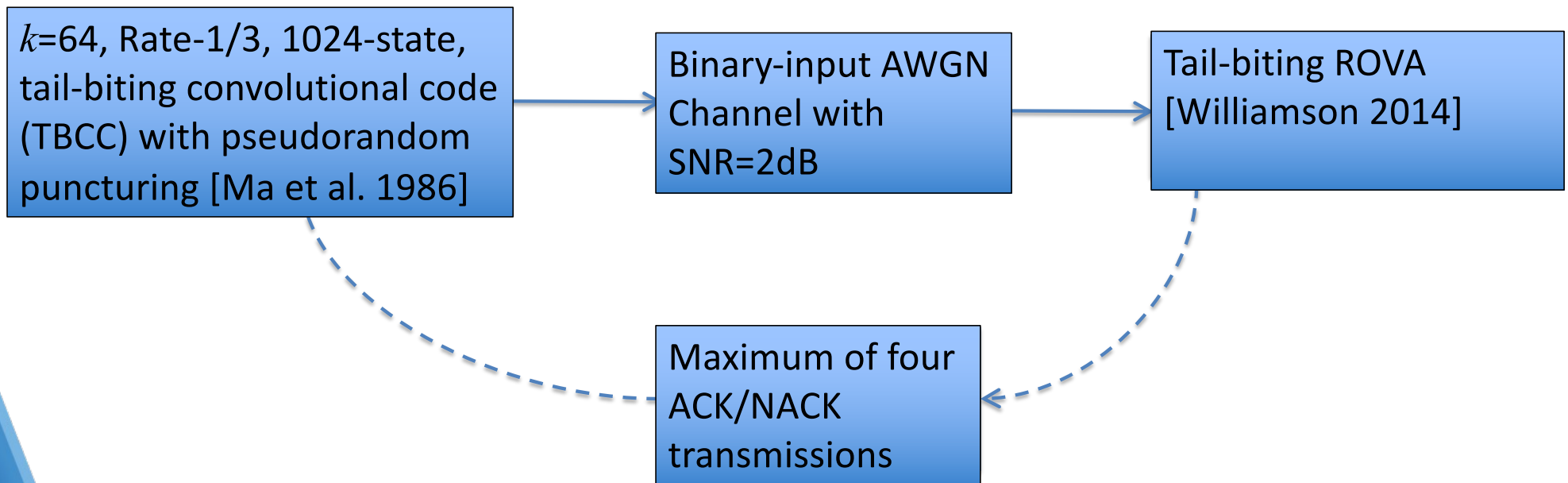
Incremental-Redundancy Hybrid ARQ



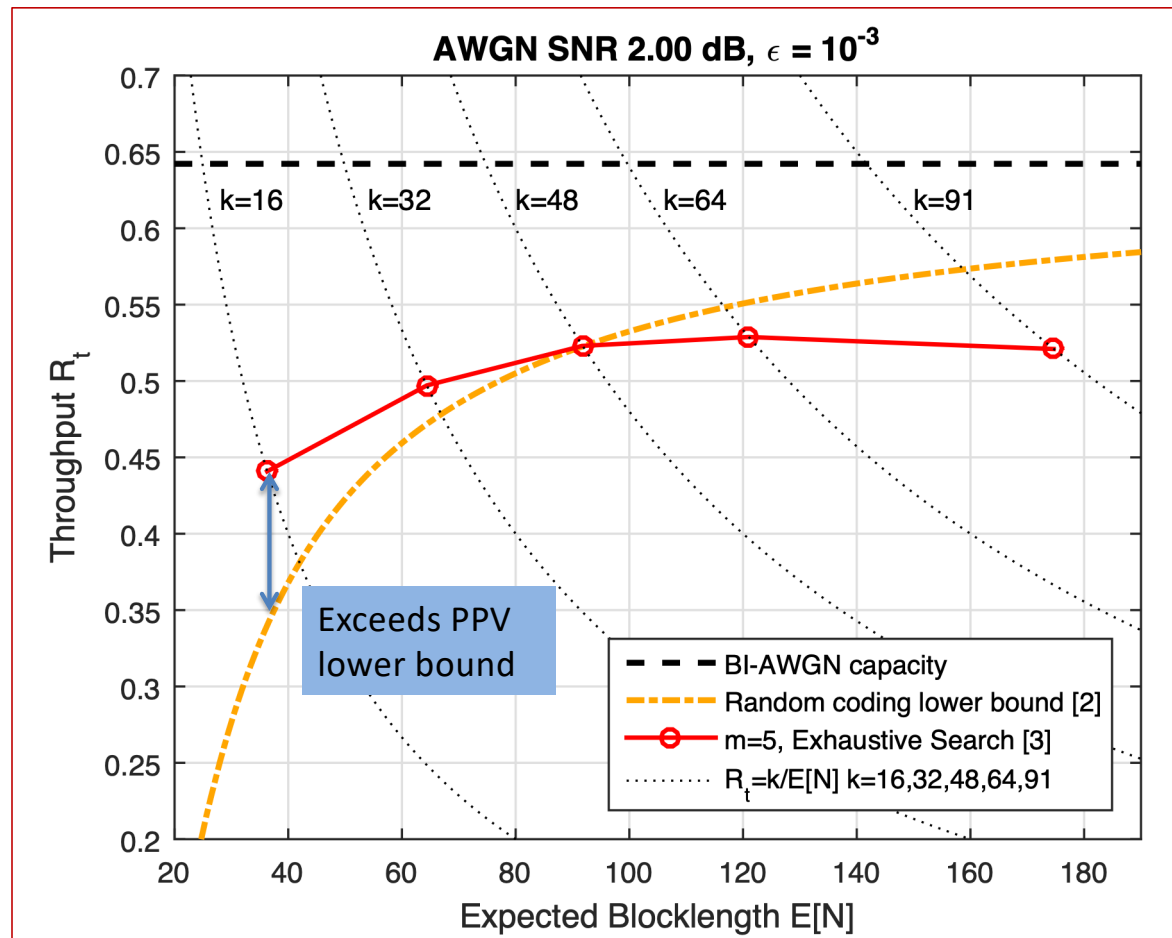
What if I am limited to five transmissions?



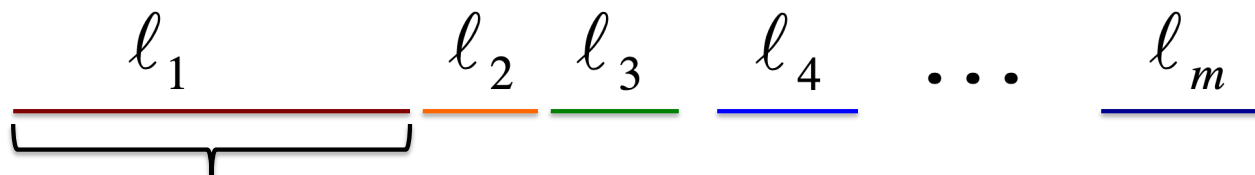
A real system [Williamson 2015]



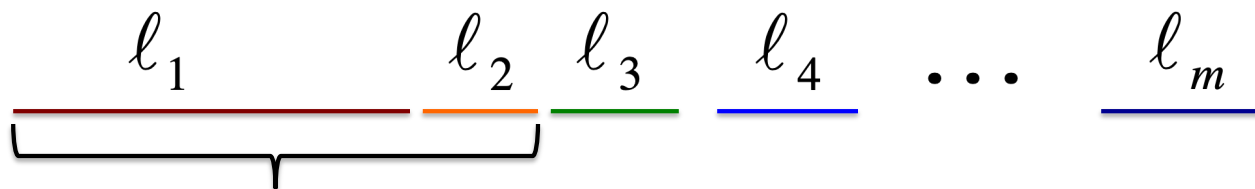
A real system [Williamson 2015]



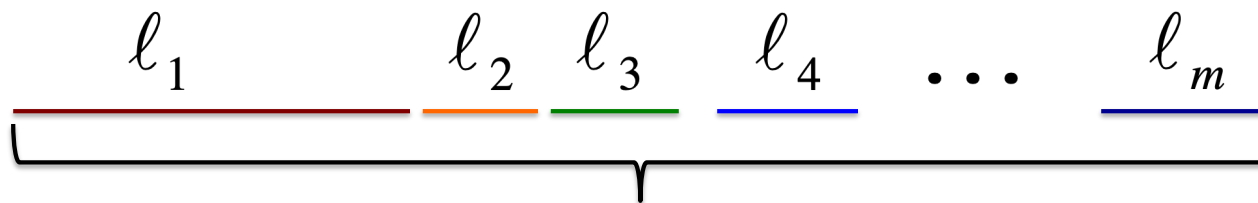
Increments and cumulative blocklengths



Increments and cumulative blocklengths



Increments and cumulative blocklengths



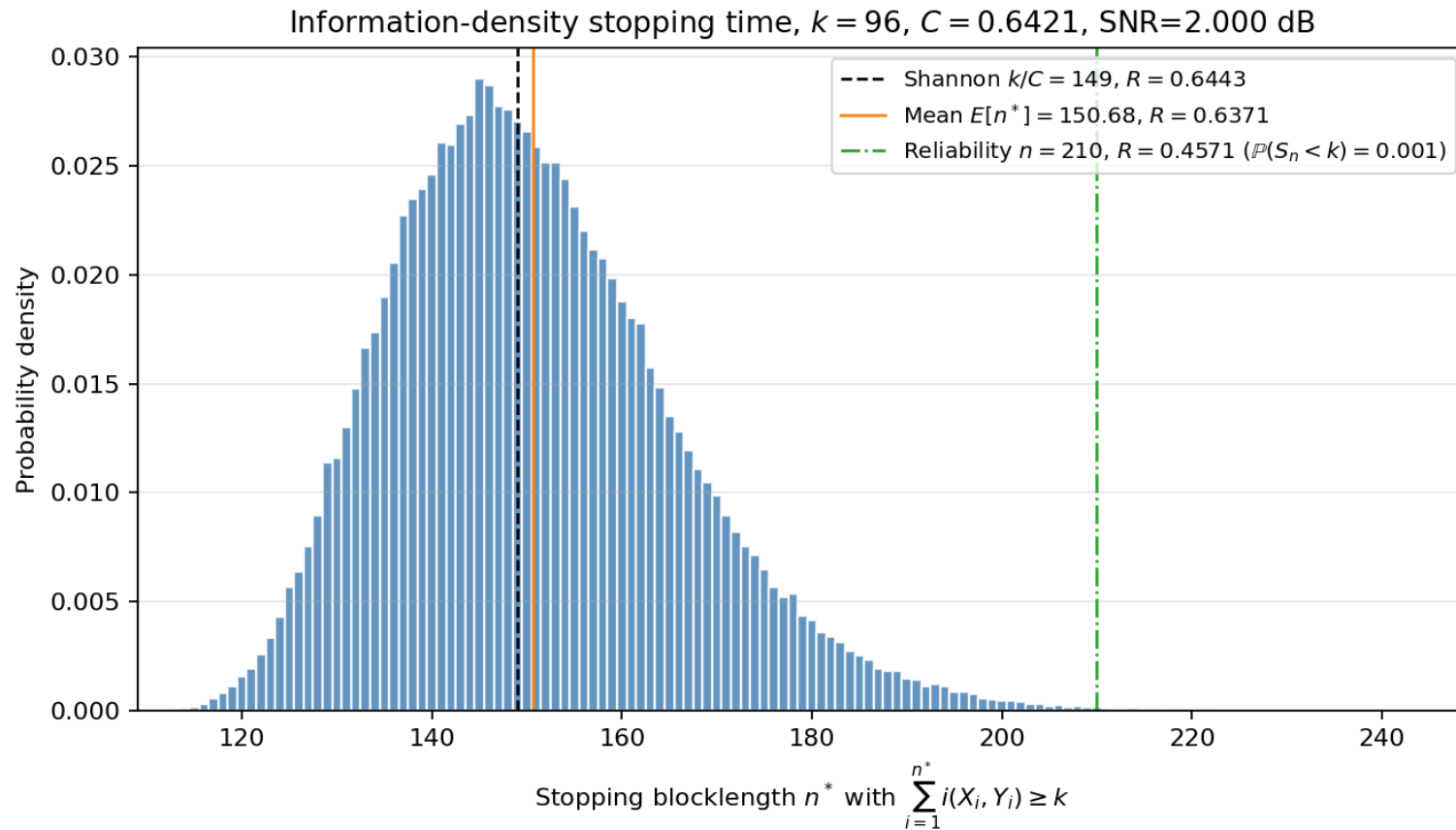
Stopping after m transmissions leads to little loss in many cases [Heindlmaier and Soljanin].

But How To Optimize Transmission Lengths?

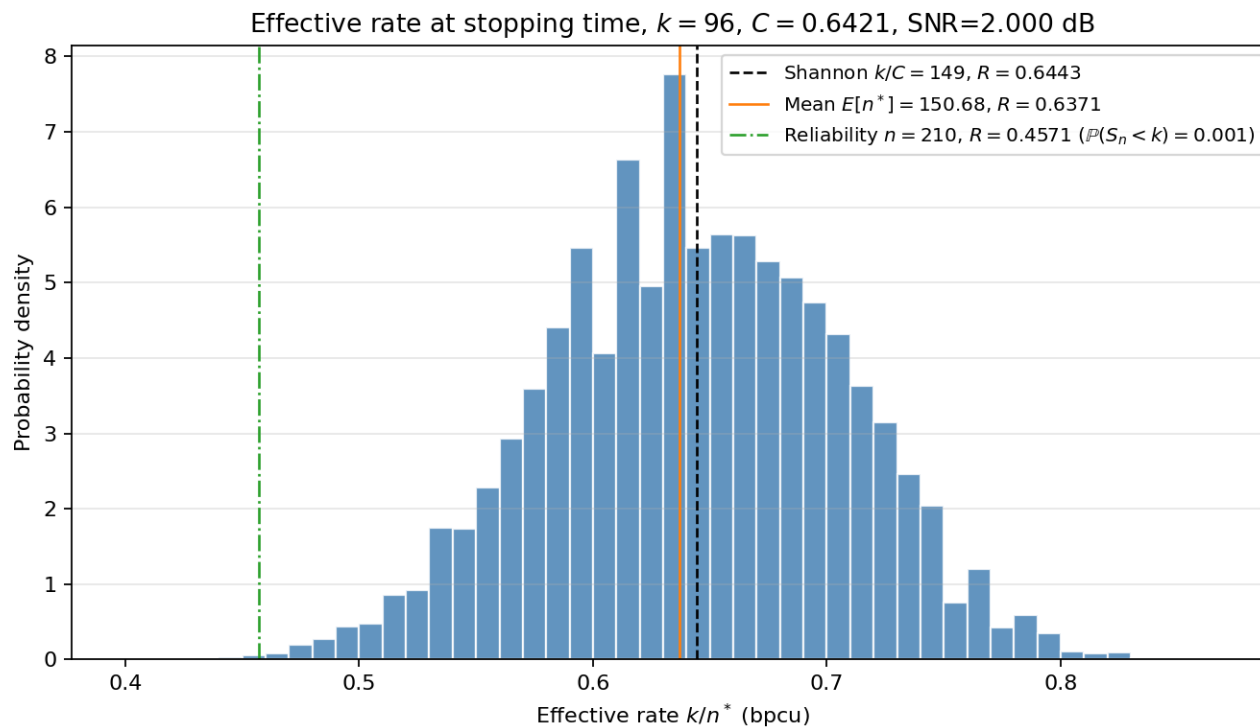
$$N_f = \sum_{j=1}^f \ell_j. \quad (1)$$

$$R_T = \frac{E[I]}{E[N]} = \frac{k \left(1 - P_{\text{NACK}}^{(m)} - P_{\text{UE}} \right)}{E[N]}, \quad (2)$$

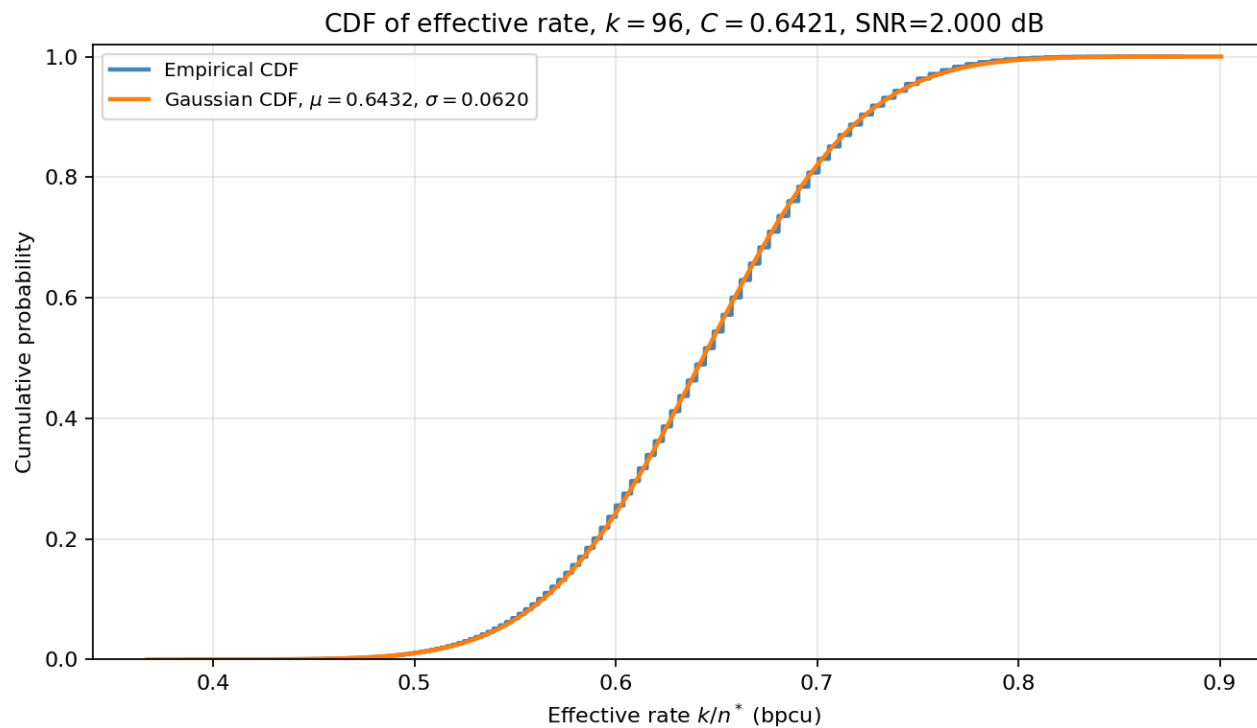
Block Length n^* where $i \geq k$: $k=96$ bits



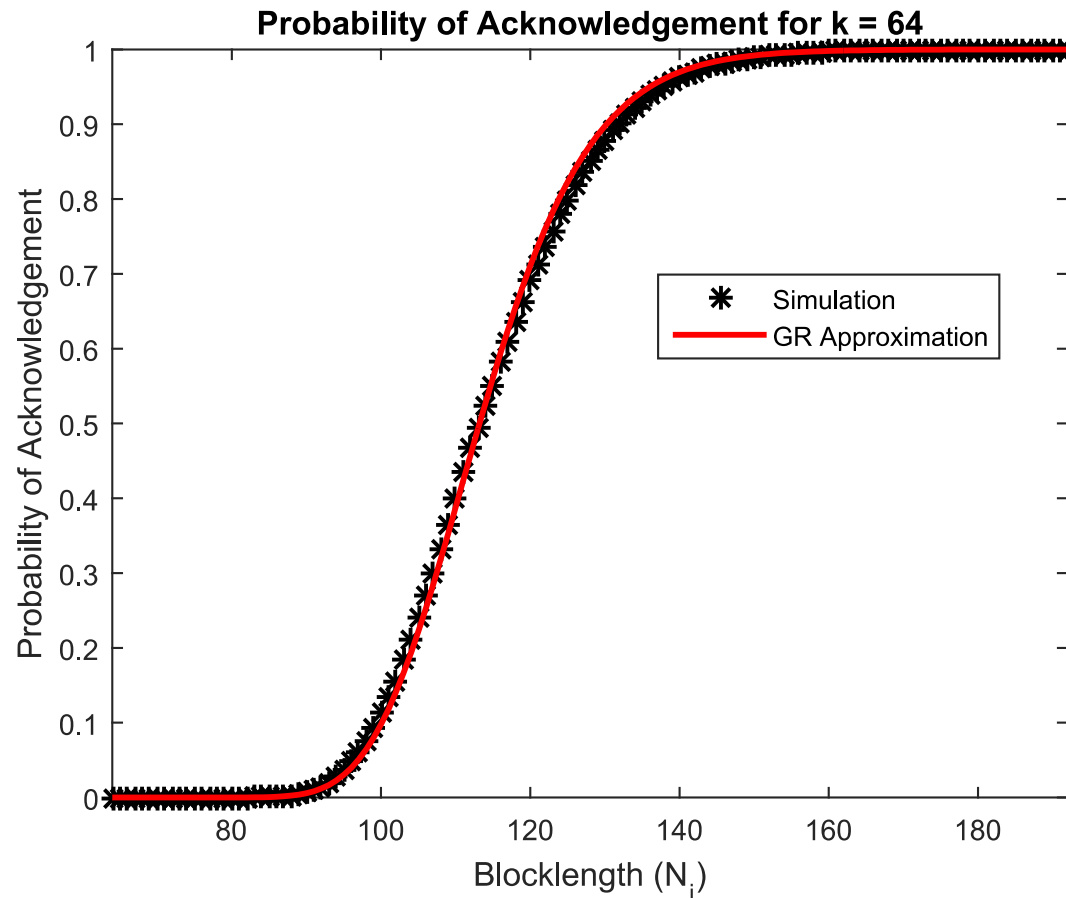
Effective rate k/n^* where $i \geq k$: $k=96$ bits



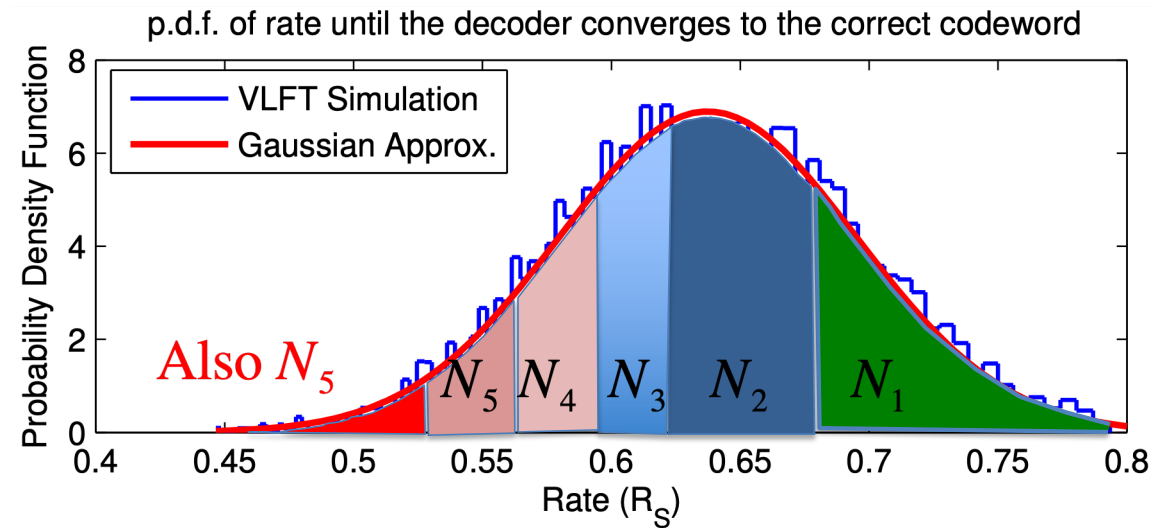
CDF of Effective rate k/n^* where $i \geq k$: $k=96$



P_{ACK} for actual code also matches Gaussian



A Closer Look at E[N]



$$E[N] = N_1 Q\left(\frac{\frac{k}{N_1} - \mu_s}{\sigma_s}\right) + \sum_{i=2}^m N_i \left[Q\left(\frac{\frac{k}{N_i} - \mu_s}{\sigma_s}\right) - Q\left(\frac{\frac{k}{N_{i-1}} - \mu_s}{\sigma_s}\right) \right] + N_m \left[1 - Q\left(\frac{\frac{k}{N_m} - \mu_s}{\sigma_s}\right) \right]$$

But How To Optimize Transmission Lengths?

$$\frac{\partial E[N]}{\partial N_1} = P_{\text{ACK}}^{(N_1)} + (N_1 - N_2)P_{\text{ACK}}^{\prime(N_1)} = 0 \quad (4)$$

But How To Optimize Transmission Lengths?

For $j > 2$, $\frac{\partial E[N]}{\partial N_{j-1}} = 0$ depends only on $\{N_{j-2}, N_{j-1}, N_j\}$ as follows:

$$\frac{\partial E[N]}{\partial N_{j-1}} = P_{\text{ACK}}^{(N_{j-1})} + (N_{j-1} - N_f)P'_{\text{ACK}}(N_{j-1}) - P_{\text{ACK}}^{(N_{j-2})}. \quad (6)$$

Sequential Differential Optimization

$$N_2 = N_1 + \frac{P_{\text{ACK}}^{(N_1)}}{P'_{\text{ACK}}(N_1)} . \quad (5)$$

$$N_j = N_{j-1} + \frac{P_{\text{ACK}}^{(N_{j-1})} - P_{\text{ACK}}^{(N_{j-2})}}{P'_{\text{ACK}}(N_{j-1})} . \quad (7)$$

Note that SDO requires a differentiable PDF for P_{ACK} .

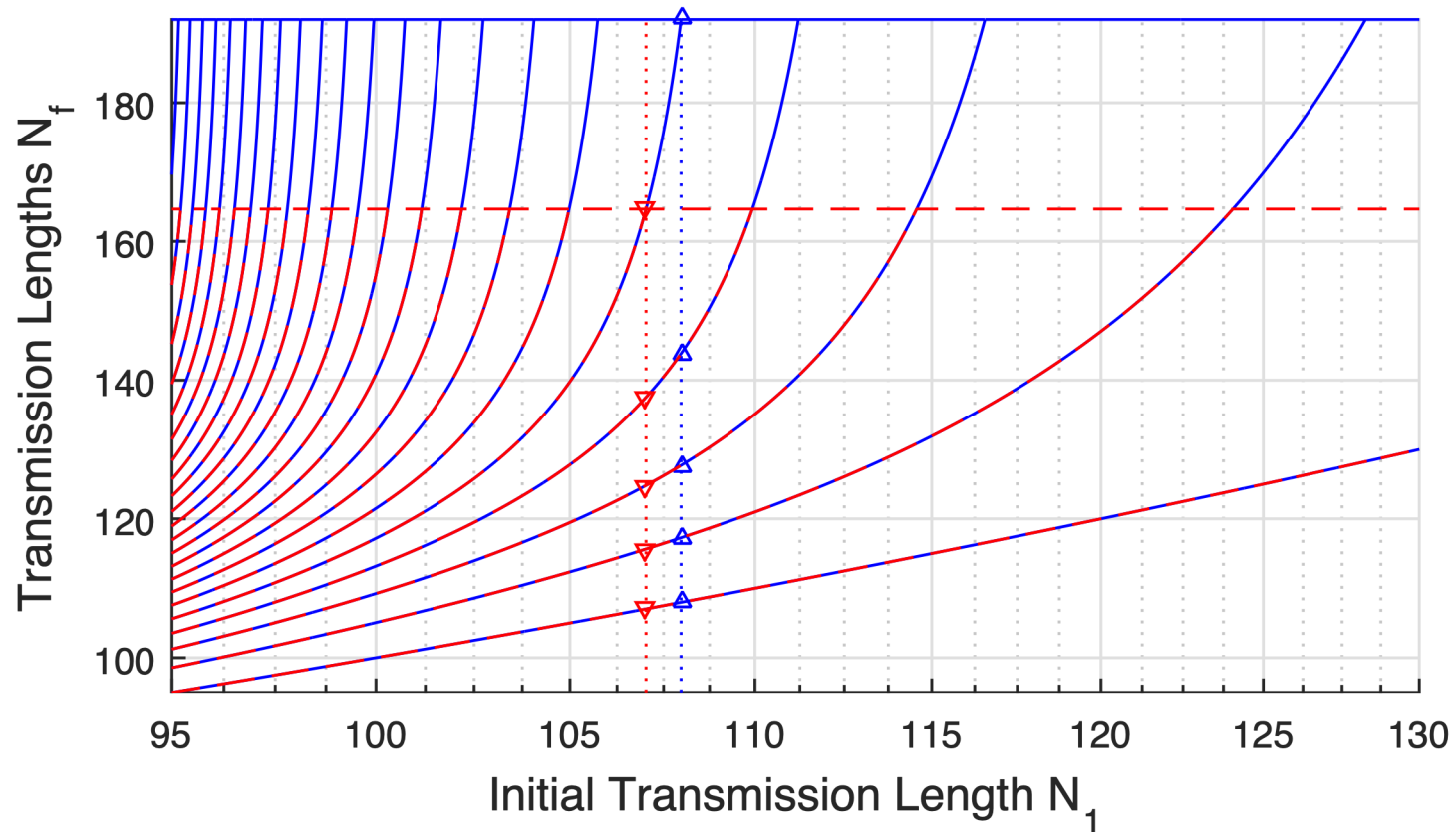
Sequential Differential Optimization

$$N_2 = N_1 + \frac{P_{\text{ACK}}^{(N_1)}}{P'_{\text{ACK}}(N_1)} . \quad (5)$$

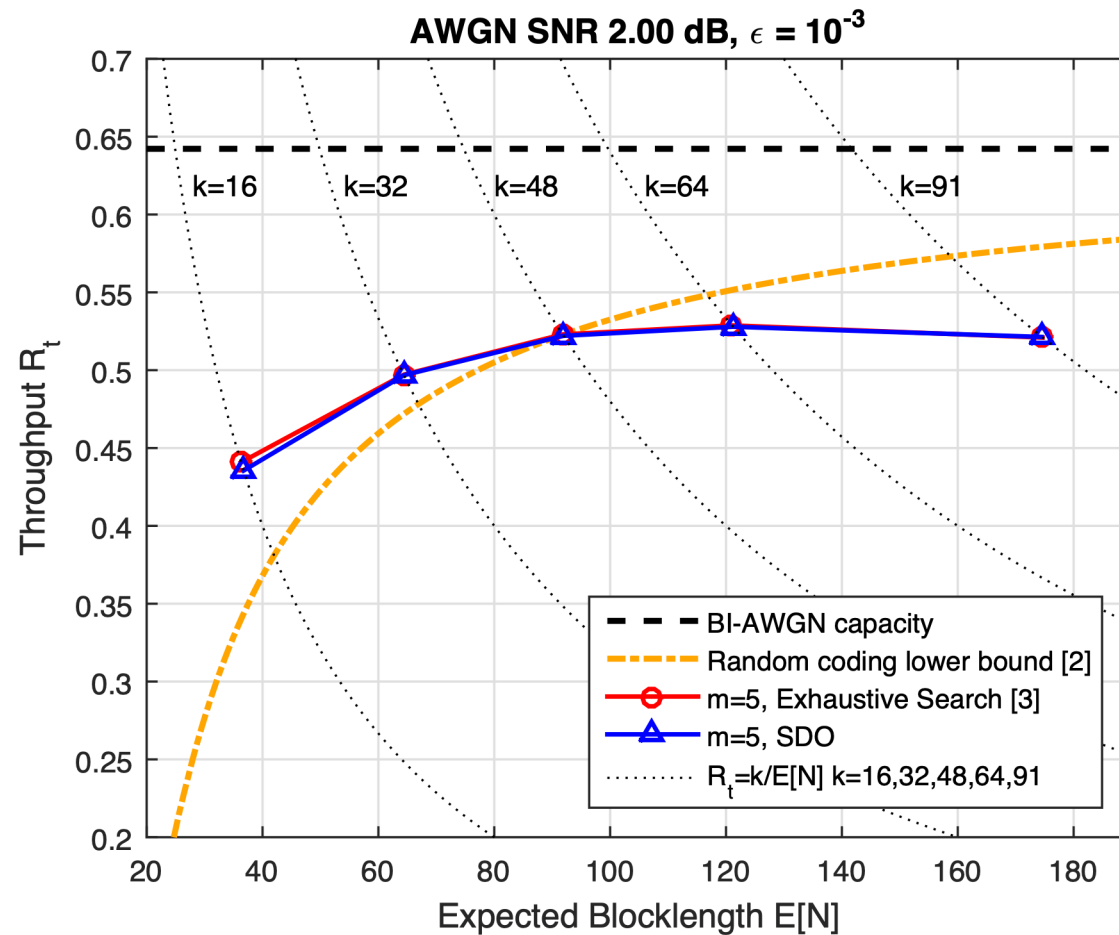
$$N_j = N_{j-1} + \frac{P_{\text{ACK}}^{(N_{j-1})} - P_{\text{ACK}}^{(N_{j-2})}}{P'_{\text{ACK}}(N_{j-1})} . \quad (7)$$

Note that SDO gives a solution for each possible value of N_1

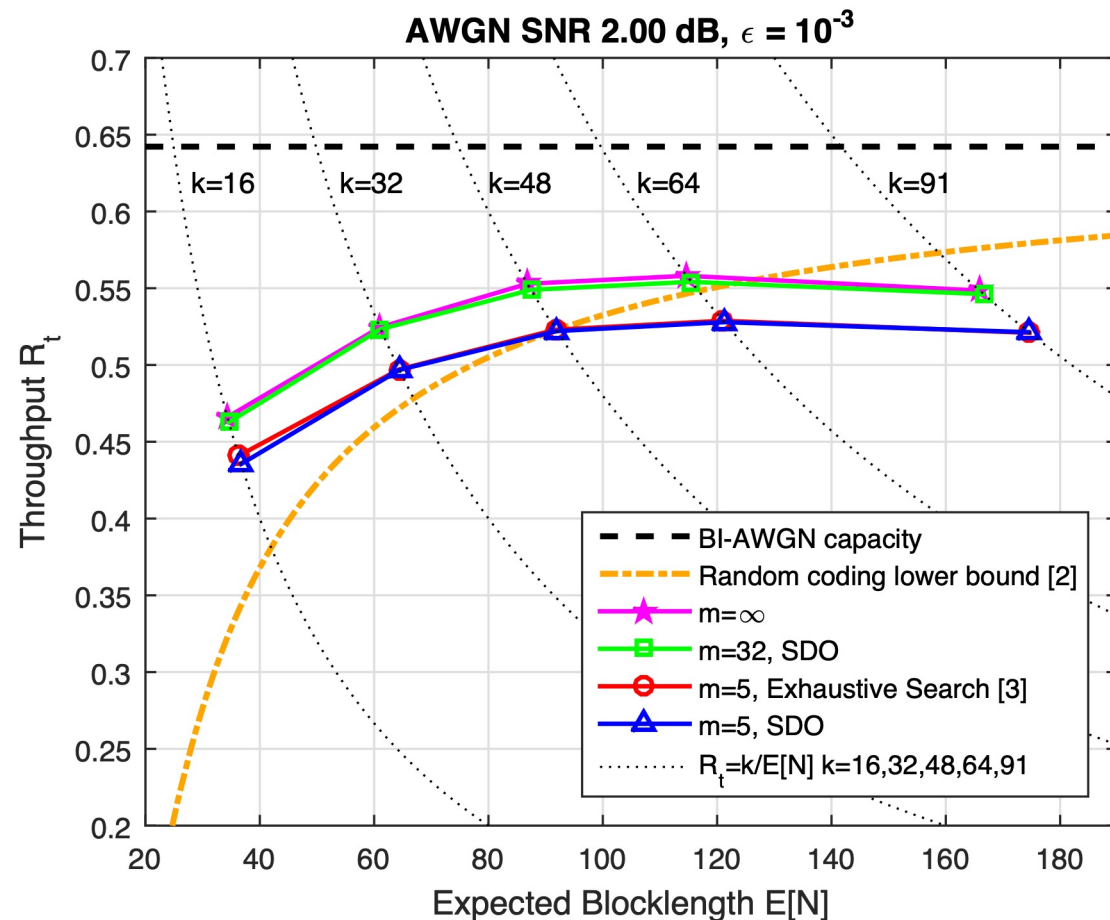
The evolution of transmission lengths



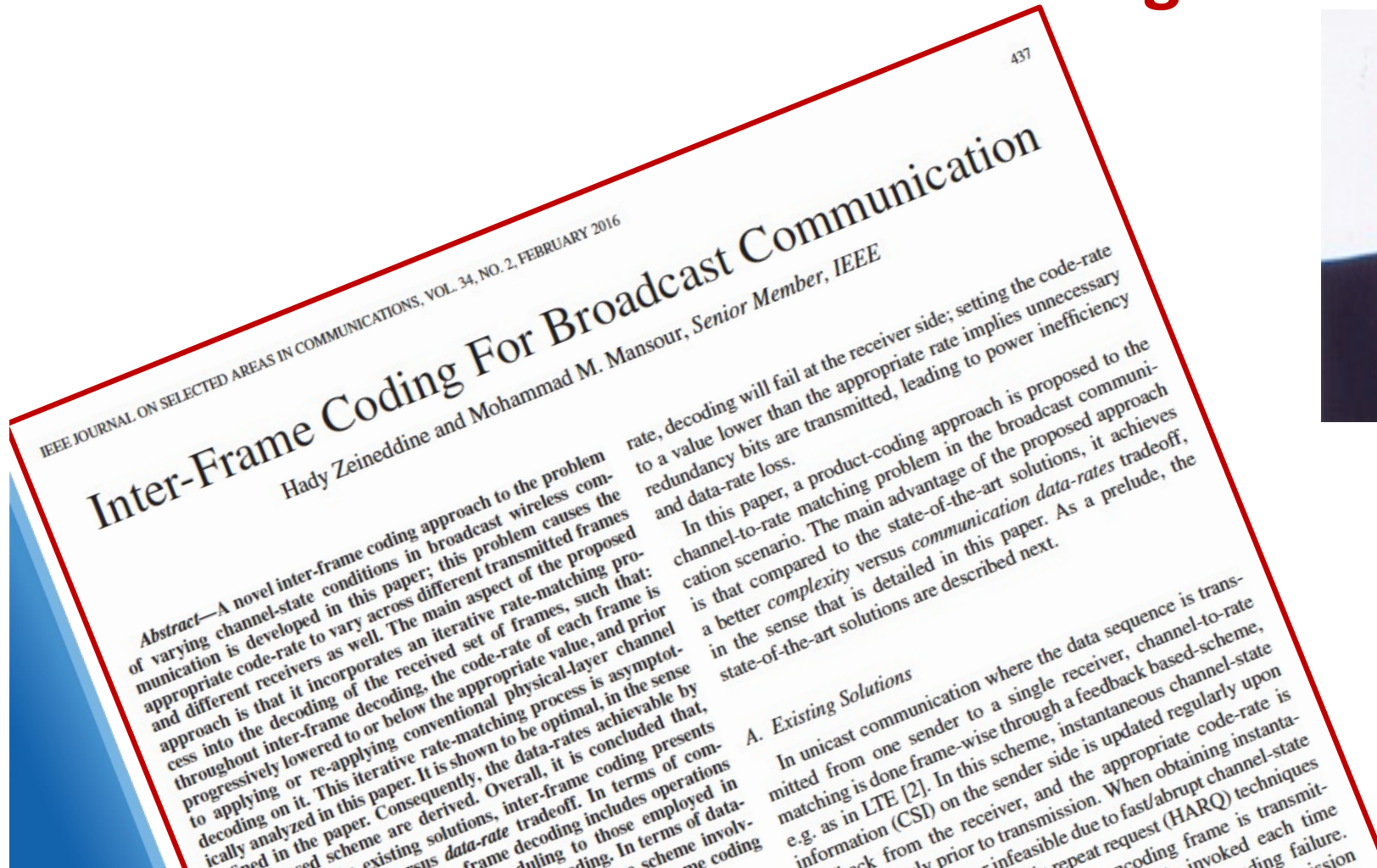
SDO matches Exhaustive Search



SDO can optimize any number of lengths



Inter-Frame Coding



Mansour

Implementation of Incremental Redundancy w/o Feedback

2017 IEEE International Symposium on Information Theory (ISIT)

Approaching Capacity Using Incremental Redundancy without Feedback

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Department of Electrical Engineering, University of California, Los Angeles, Los Angeles, California 90095
Email: {whb12, sudarsanvsr, wesel}@ucla.edu

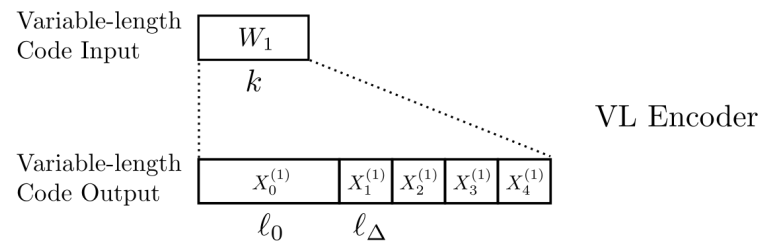
Abstract—Variable-length codes with incremental redundancy controlled by feedback allow a system to approach capacity with short average blocklengths and thus relatively low-complexity decoders. This paper shows how to use those same variable-length codes with incremental redundancy to approach capacity without feedback. The general principle is to provide a common pool of redundancy that can be accessed by exactly the variable-length codes that need it. We provide example implementations using both regular and irregular low-density generator matrices (LDGM) codes to provide this common pool of redundancy, utilizing the inter-frame coding variation due to fading in broadcast transmissions. The LDGM degree distribution requires a new design involving differential evolution for a generalized binary noise channel. Monte Carlo simulations confirm the feasibility of the proposed approach, showing a frame error rate of 10^{-3} and a throughput of the channel.

As described above, a well-known benefit of feedback is that capacity can be approached with a short average blocklength. The approach described in this paper does not use feedback and thus cannot accrue that benefit precisely. Rather, the overall system described in this paper has a blocklength that is fixed and, typically, rather long. The real benefit of the proposed approach is that much of the processing that happens at the receiver can be distributed to a large number of decoders operating (perhaps in parallel) on individual VL codes that do have short average blocklengths. Thus, the approach seeks to provide long-blocklength performance (i.e. by approaching capacity without feedback) with short-blocklength decoders. Consider a transmitter sending a fixed number of VL codes in parallel. Appealing to ergodicity, the overall amount of IR needed by a large number of VL codes operating on a discrete memoryless channel can be computed with high confidence. The remaining issue is to ensure that the transmitted IR can be used by the VL codes that need it. The novel inter-frame approach of Zeineddine and Mansour [6] transmits combinations of constant-length IR sequences to combat fading in broadcast transmissions, without applying this approach to a smaller time scale. The symbol-by-symbol approach of Zeineddine and Mansour [6] transmits combinations of constant-length IR sequences to combat fading in broadcast transmissions, without applying this approach to a smaller time scale. The symbol-by-symbol approach of Zeineddine and Mansour [6] transmits combinations of constant-length IR sequences to combat fading in broadcast transmissions, without applying this approach to a smaller time scale.

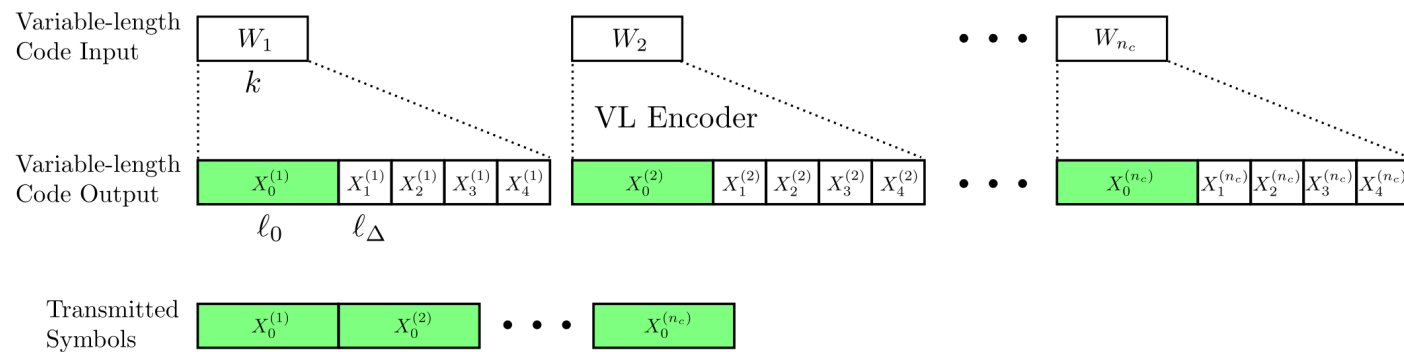


Haobo Wang

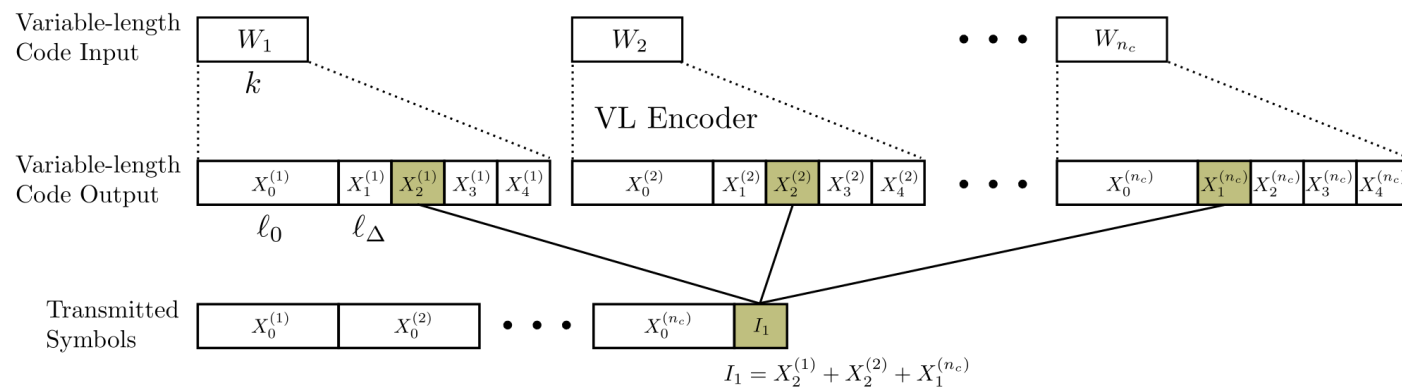
Inter-frame Coding



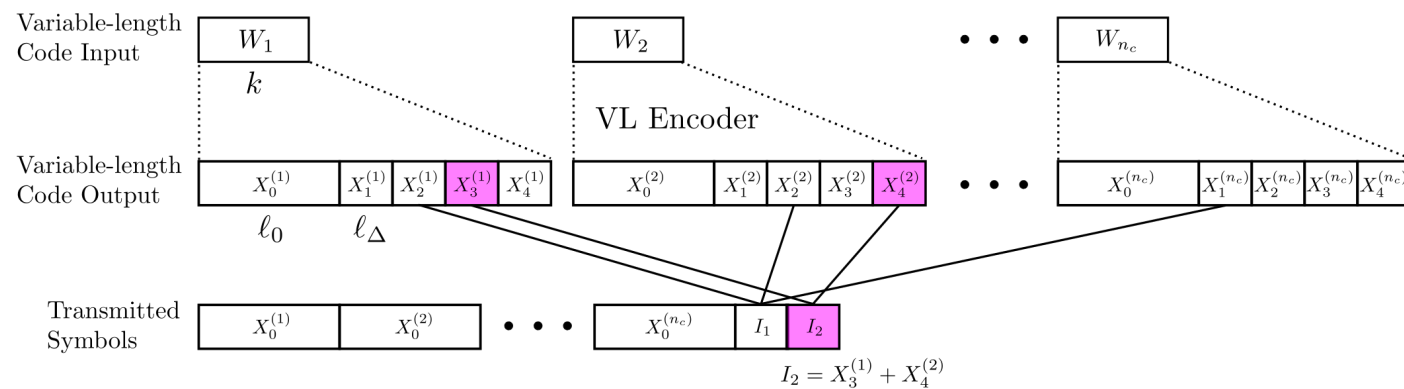
Inter-frame Coding



Inter-frame Coding

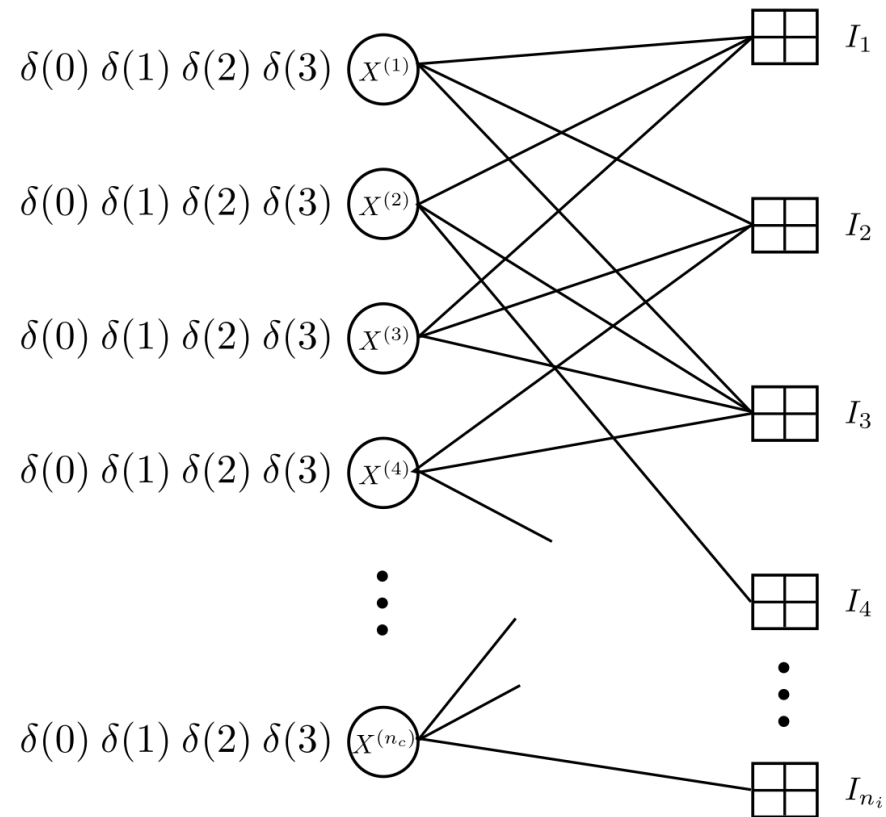


Inter-frame Coding



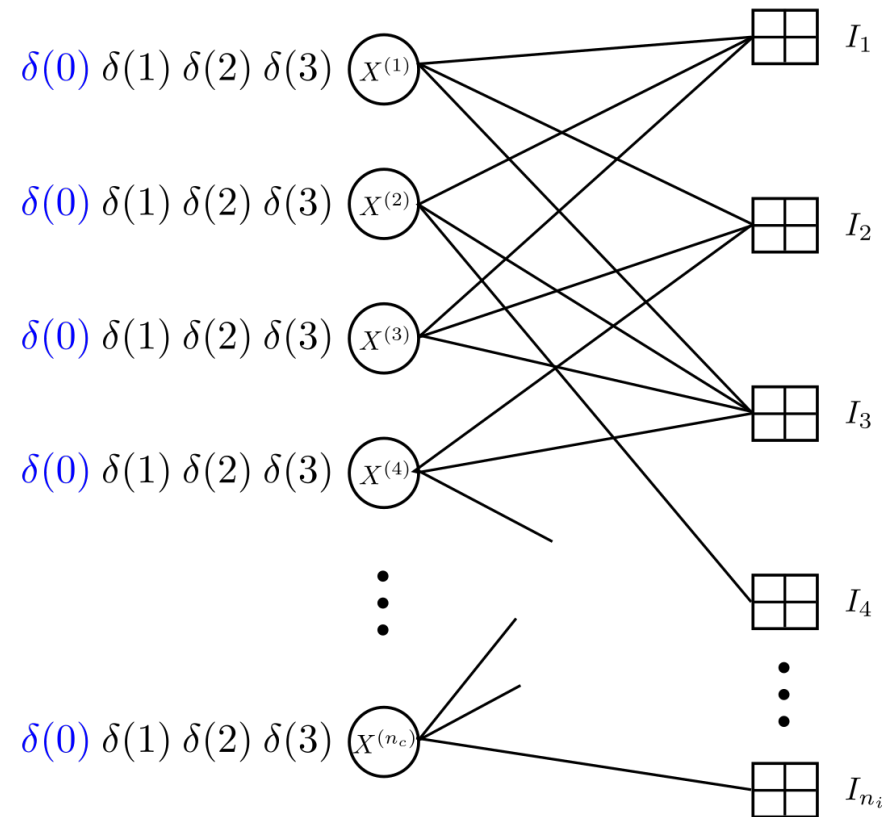
Inter-frame Coding: Peeling Decoder

$m = 3$



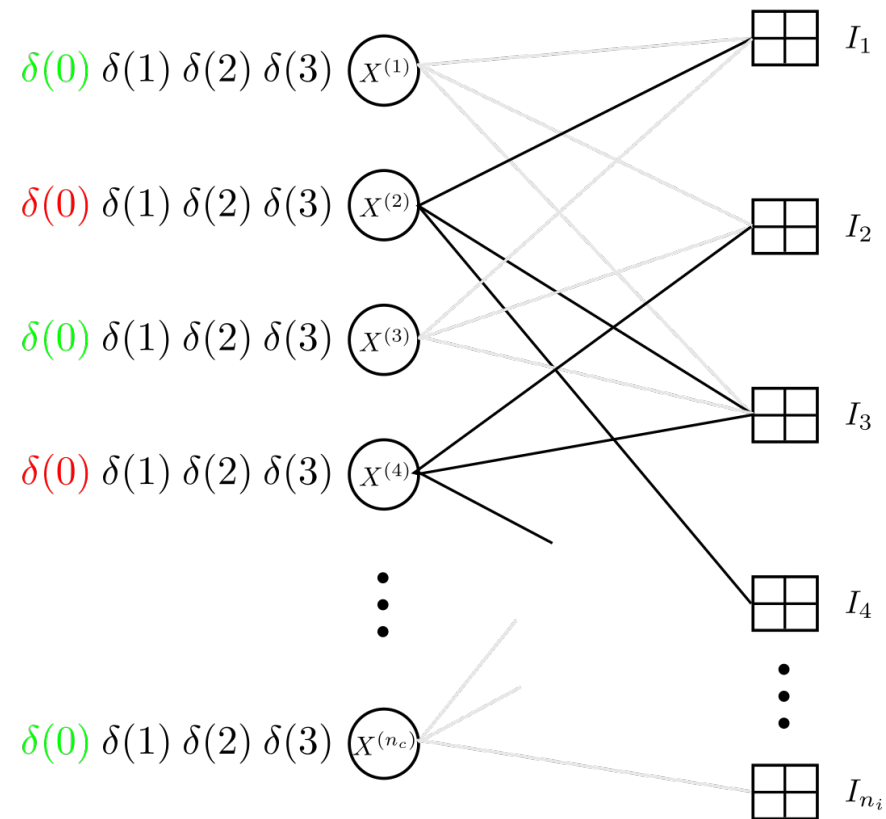
Inter-frame Coding: Peeling Decoder

Attempting decoding
Decoding Succeeded
Decoding Failed



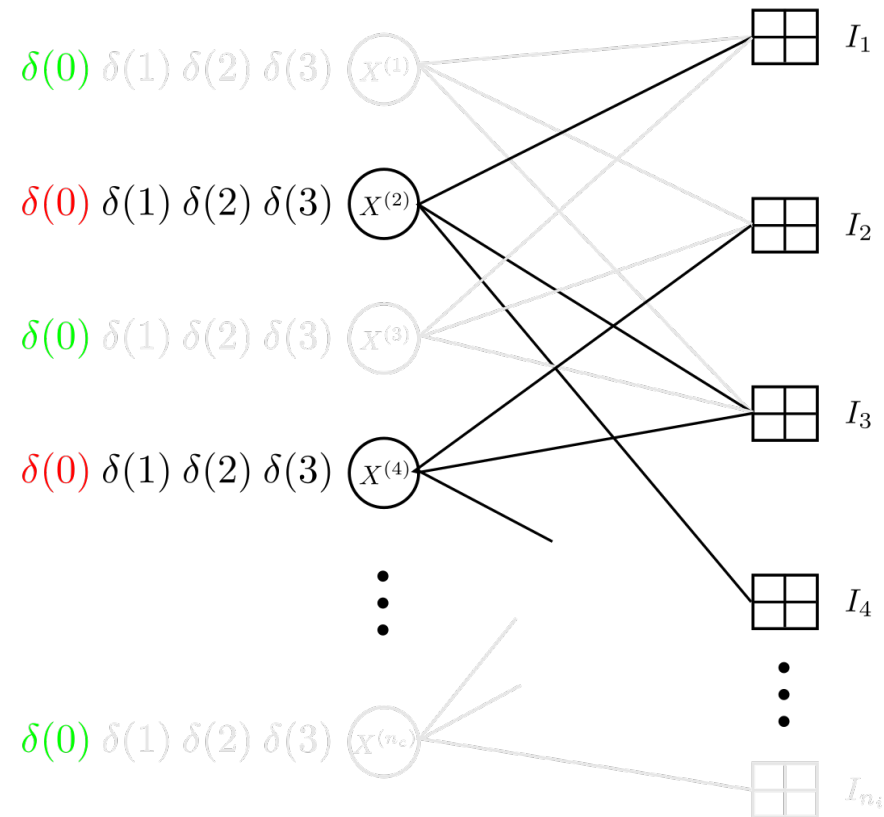
Inter-frame Coding: Peeling Decoder

Attempting decoding
Decoding Succeeded
Decoding Failed



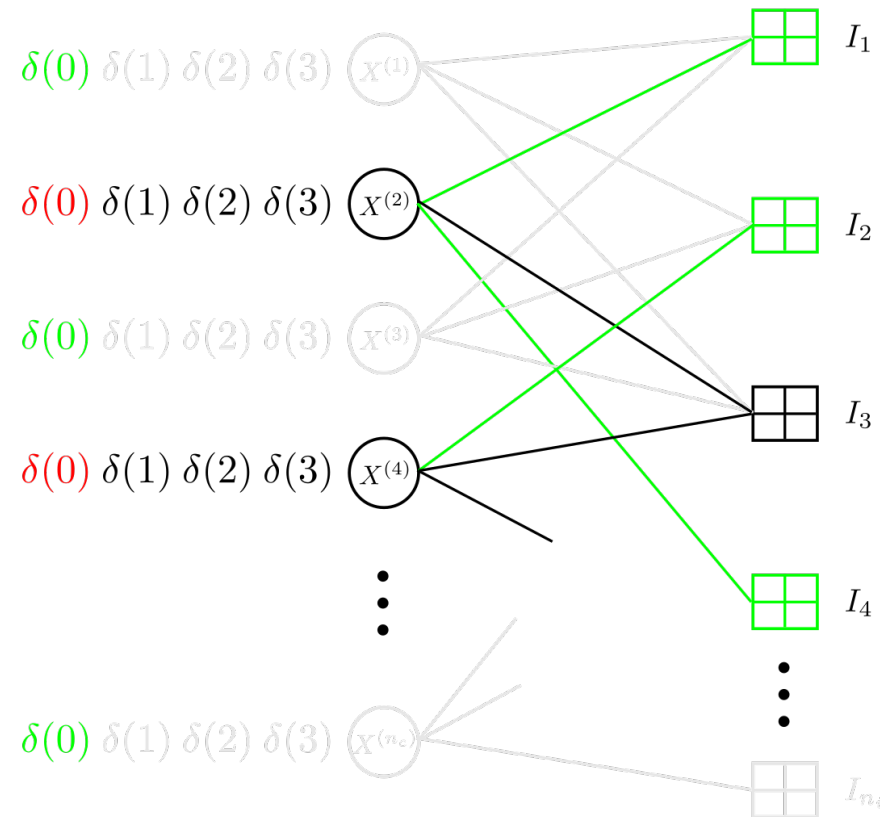
Inter-frame Coding: Peeling Decoder

Attempting decoding
Decoding Succeeded
Decoding Failed



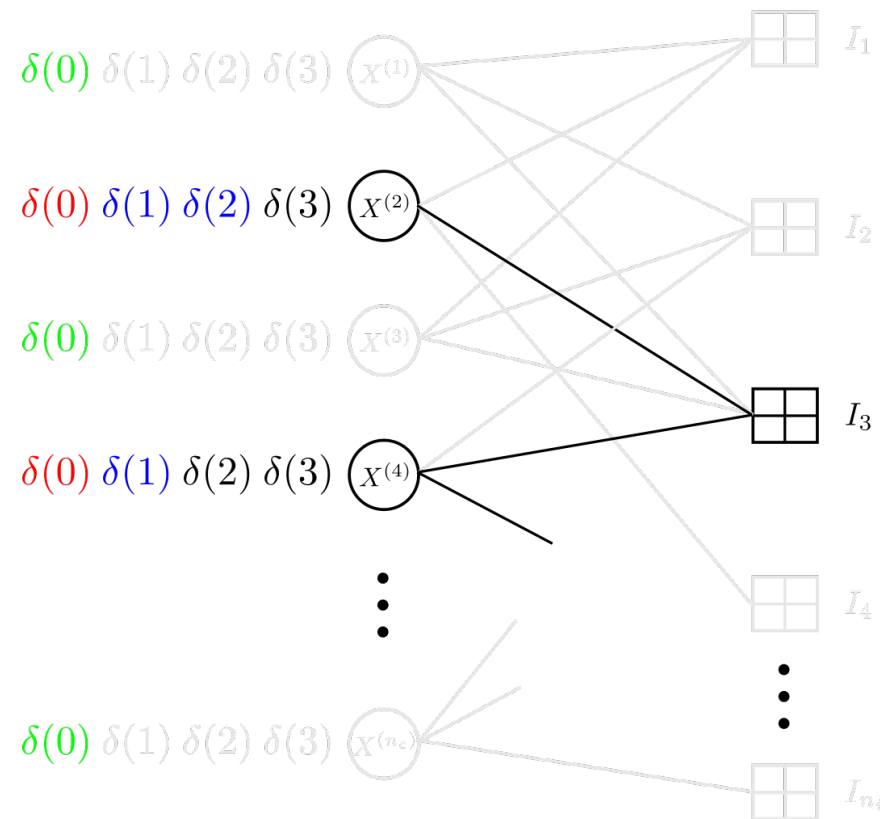
Inter-frame Coding: Peeling Decoder

Attempting decoding
Decoding Succeeded
Decoding Failed



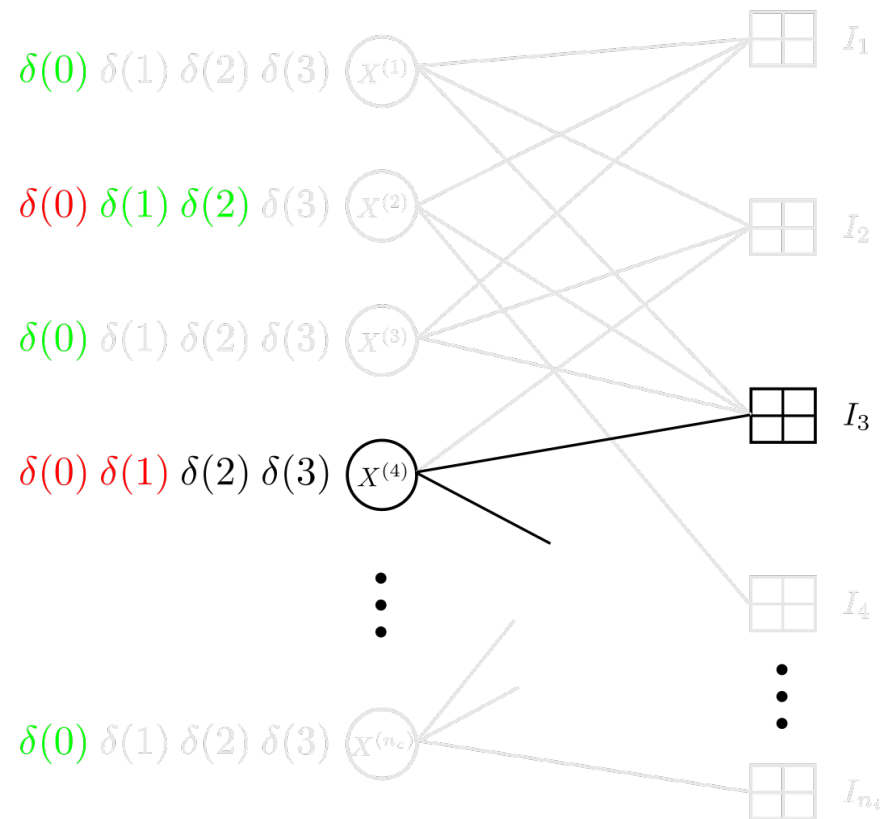
Inter-frame Coding: Peeling Decoder

Attempting decoding
Decoding Succeeded
Decoding Failed



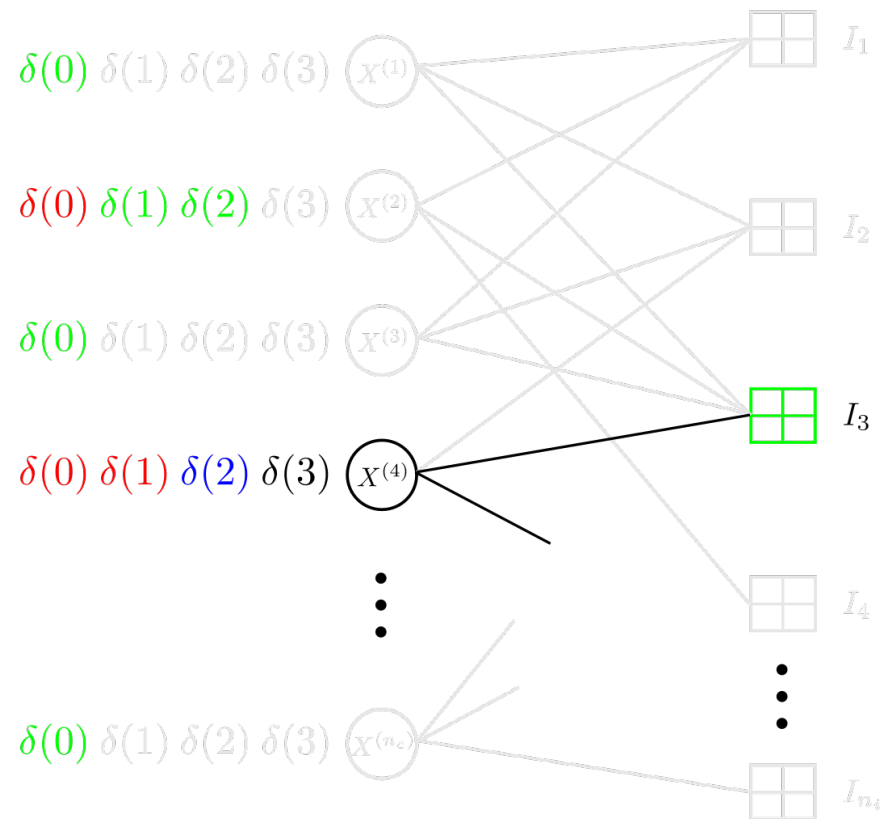
Inter-frame Coding: Peeling Decoder

Attempting decoding
Decoding Succeeded
Decoding Failed



Inter-frame Coding: Peeling Decoder

Attempting decoding
Decoding Succeeded
Decoding Failed



Stop Feedback Summary

- For short messages, stop feedback dramatically increases achievable rate.
- This is because it allows a variable-length code that stops when a reliable decision is available.
- The theoretical analysis assumes we check accumulated information density for every codeword after every symbol
- But real systems can achieve similar performance by checking decoder reliability at a few key times determined by sequential differential optimization.
- You can also use many variable-length short codes in parallel and use linear combinations of increments and a peeling decoder to avoid using feedback



Act 3:

Full feedback further increases the rate of short messages that achieve a target reliability

Full Feedback

- Stop Feedback increases achievable rate by stopping transmission as soon as possible
- Full feedback also does this, but *additionally* increases achievable rate by avoiding telling the receiver things that it already knows.

Horstein's Full Feedback Algorithm for the BSC

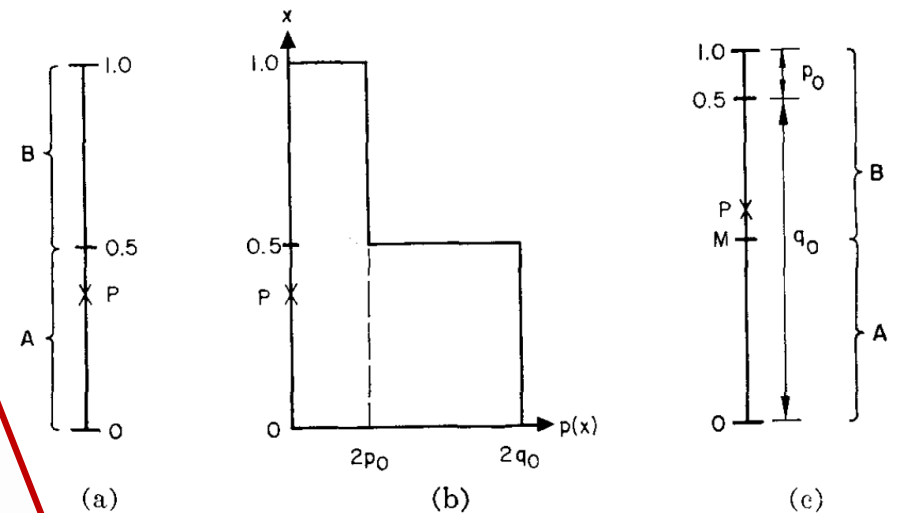


Fig. 2—Selection of the transmitted symbol.

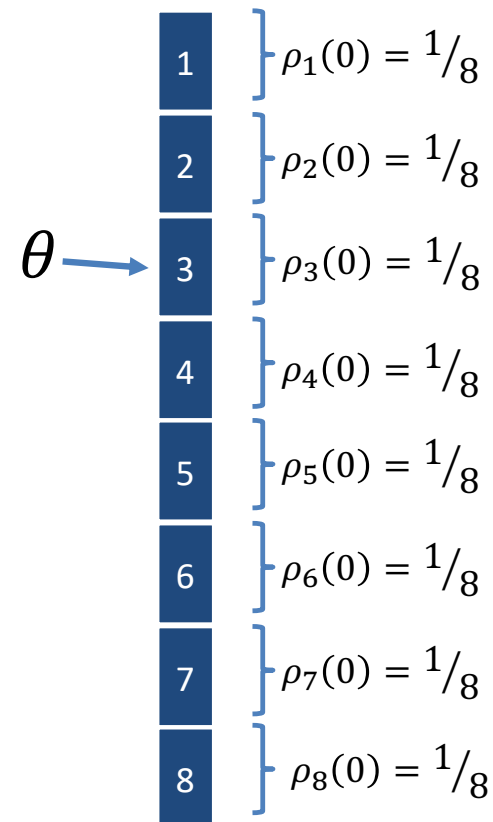
From Horstein Trans. IT 1963

Make sure each transmitted bit is conveying a full bit of useful information in light of what the receiver already knows.

Finite blocklength sequential transmission

AN EIGHT-MESSAGE EXAMPLE ON THE BSC

- There are $M = 2^k$ messages $\{1, 2, \dots, M\}$.
- The true message is θ .
- The original prior probabilities are all $\rho_i(0) = 2^{-k}$.



Finite blocklength sequential transmission

AN EIGHT-MESSAGE EXAMPLE ON THE BSC

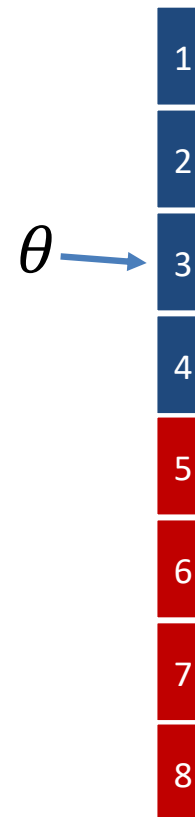
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Finite blocklength sequential transmission

AN EIGHT-MESSAGE EXAMPLE ON THE BSC

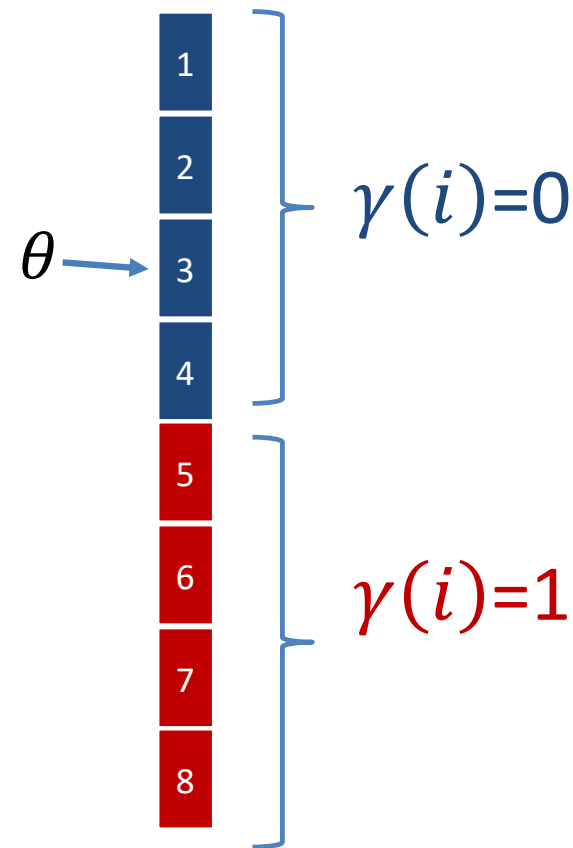
- There are $M = 2^k$ messages $\{1, 2, \dots, M\}$.
- The true message is θ .
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- Divide the interval into two sets, **Set 0** and **Set 1**, Each having probability $\frac{1}{2}$.



Finite blocklength sequential transmission

AN EIGHT-MESSAGE EXAMPLE ON THE BSC

- There are $M = 2^k$ messages $\{1, 2, \dots, M\}$.
- The true message is θ .
- The original prior probabilities are all $\rho_i(0) = 2^{-k}$.
- Divide the interval into two sets, **Set 0** and **Set 1**, Each having probability $\frac{1}{2}$.
- Transmit $\gamma(\theta)$, which is a **0** if θ is in S_0 and transmit a **1** if θ is in S_1 .



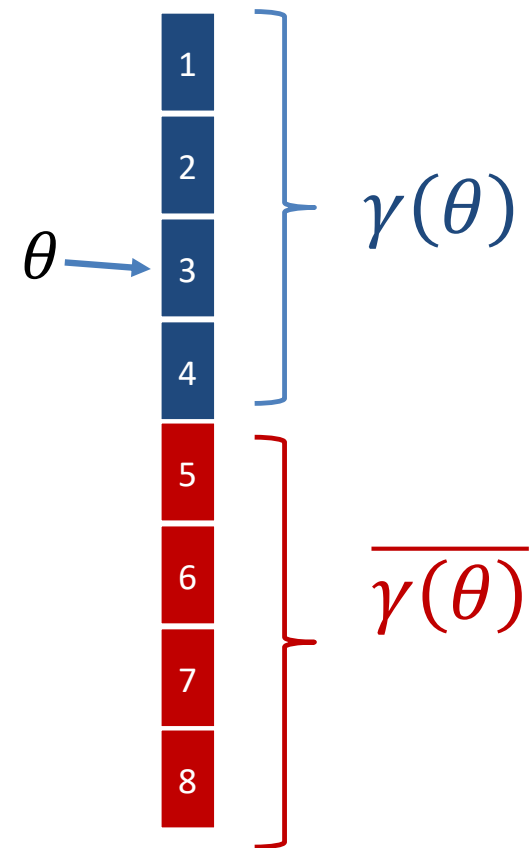
Computing the posterior $\rho_i(n + 1)$ from $\rho_i(n)$

- It's a BSC with probability of error p so

$$Y = \begin{cases} \gamma(\theta) & \text{with probability } q = 1 - p \\ \overline{\gamma(\theta)} & \text{with probability } p. \end{cases}$$

- The posteriors are updated as follows:

$$\rho_i(n + 1) = \begin{cases} \frac{\rho_i(n)P(Y = \gamma(i)|i)}{P(Y = \gamma(i))} & \text{when } Y = \gamma(i) \\ \frac{\rho_i(n)P(Y = \overline{\gamma(i)}|i)}{P(Y = \overline{\gamma(i)})} & \text{when } Y = \overline{\gamma(i)} \end{cases}$$

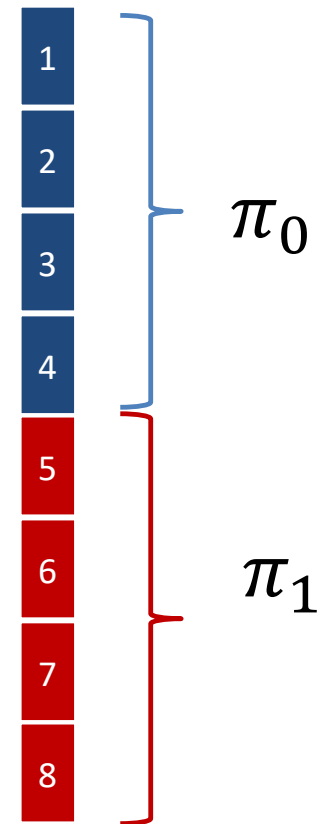


Computing marginal output probabilities $P(Y)$

MARGINAL OUTPUT PROBABILITIES FOR THE BSC

- Define the marginal probabilities of S_0 and S_1 .
- $\pi_0 = P(S_0)$
- $\pi_1 = P(S_1)$
- It's a BSC with probability of error p so

$$P(Y) = \begin{cases} \pi_0 q + \pi_1 p & \text{for } Y = 0 \\ \pi_0 p + \pi_1 q & \text{for } Y = 1 \end{cases}$$

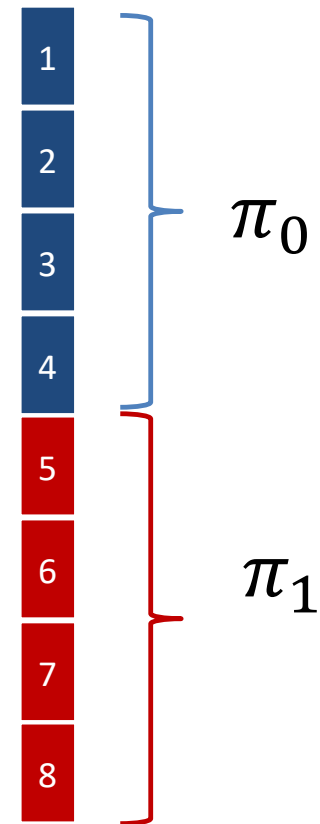


Computing the posterior $\rho_i(n + 1)$ from $\rho_i(n)$

MARGINAL OUTPUT PROBABILITIES FOR THE BSC

- But if things are going well.
- $\pi_0 = 1/2$
- $\pi_1 = 1/2$

- $$P(Y) = \begin{cases} 1/2 & \text{for } Y = 0 \\ 1/2 & \text{for } Y = 1 \end{cases}$$



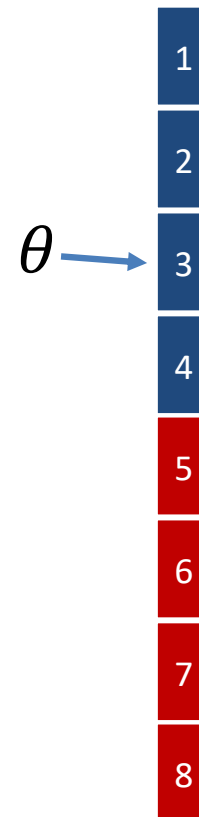
Computing the posterior $\rho_i(n + 1)$ from $\rho_i(n)$

- The posteriors are updated as follows:

$$\rho_i(n + 1) = \begin{cases} \frac{\rho_i(n)q}{P(Y = \gamma(i))} \\ \frac{\rho_i(n)p}{P(Y = \overline{\gamma(i)})} \end{cases}$$

when $Y = \gamma(i)$

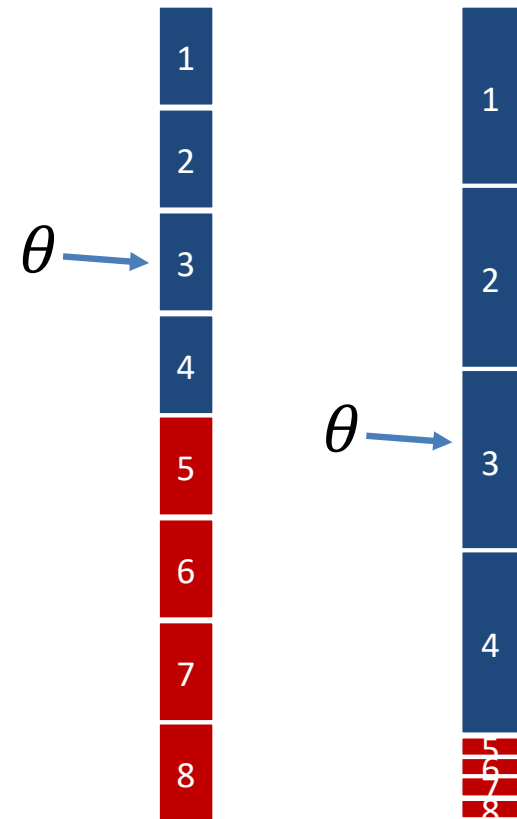
when $Y = \overline{\gamma(i)}$



Computing the posterior $\rho_i(n + 1)$ from $\rho_i(n)$

- The posteriors are updated as follows:

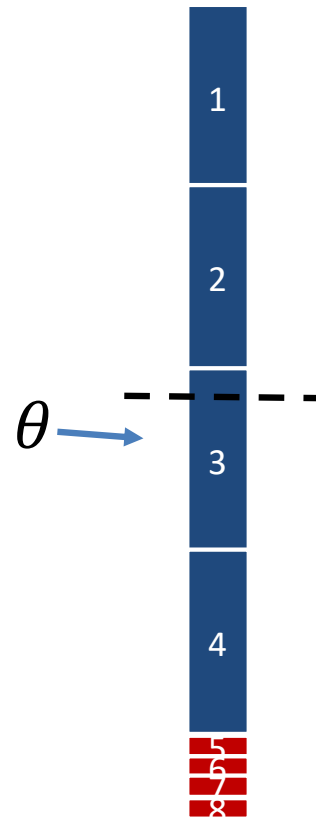
$$\rho_i(n + 1) = \begin{cases} \rho_i(n)2q & \text{when } Y = \gamma(i) \\ \rho_i(n)2p & \text{when } Y = \overline{\gamma(i)} \end{cases}$$



Horstein's assignment* to S_0 and S_1

SOMETIMES THE MEDIAN LINE DIVIDES A MESSAGE

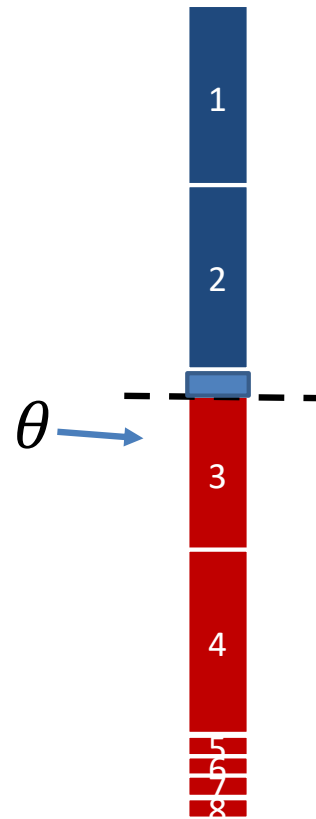
In this case Hornstein performs random encoding



Horstein's assignment* to S_0 and S_1

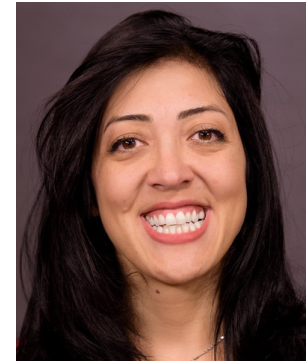
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DOI: 10.1214/13-AOS1144
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of the classical se-

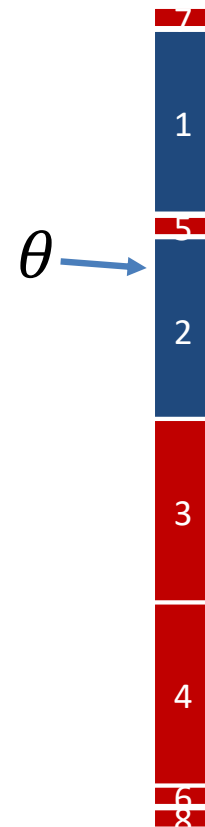


Javidi

Reordering (Naghshvar's MaxEJS)

BUT THERE ARE MANY SMALL MESSAGES

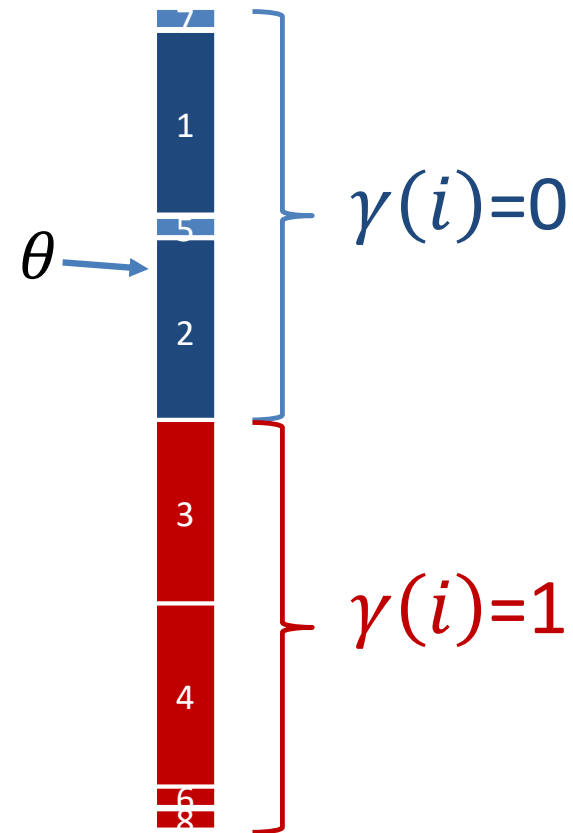
Naghshvar et al. simply move the messages around to allow a nice split right at (or very near to) $\frac{1}{2}$.



Reordering (Naghshvar's MaxEJS)

BUT THERE ARE MANY SMALL MESSAGES

Naghshvar et al. simply move the messages around to allow a nice split right at (or very near to) $\frac{1}{2}$.



Finally, a non-asymptotic bound

Extrinsic Jensen-Shannon Divergence

The Extrinsic Jensen-Shannon (EJS) Divergence is a metric that indicates how informative a transmitted symbol will be.

By maximizing EJS, Naghshvar, Javidi, and Wigger provide a version of Horstein's algorithm that can be analyzed non-asymptotically

Solves the “coin-weighting” problem for every transmission by REORDERING the messages.

Extrinsic Jensen-Shannon Divergence: Applications to Variable-Length Coding

Mohammad Naghshvar, Member, IEEE, Tara Javidi, Senior Member, IEEE, and Michèle Wigger, Senior Member, IEEE

Abstract—This paper considers the problem of variable-length coding over a discrete memoryless channel with noiseless feedback. This paper provides a stochastic control view of the problem whose solution is analyzed via a newly proposed symmetrized divergence, termed extrinsic Jensen-Shannon (EJS) divergence. It is shown that strictly positive lower bounds on the expected code length, for the following two coding schemes: 1) variable-length posterior matching and 2) MaxEJS coding scheme that is based on a greedy maximization of the EJS divergence, and hence nonasymptotic upper bounds on the expected code length. Variable-length coding schemes achieving capacity and optimal error exponent, for parameters R and E are guaranteed to achieve a rate R and an error exponent E . The results are specialized for posterior matching and MaxEJS to obtain deterministic one-phase coding schemes achieving capacity and optimal error exponent. For the special case of symmetric binary-input channels, simpler deterministic schemes of optimal performance are proposed and analyzed.

Index Terms—Discrete memoryless channel, variable-length coding, sequential analysis, feedback gain, Burnashev's reliability function, optimal error exponent.

INTRODUCTION

Upper and lower bounds on the channel uses $E[\tau_n^*]$ for a given message n are then

the DMC, the ratio between the upper and lower bounds approaches 1 as $\epsilon \rightarrow 0$. Therefore, the bounds yield the optimal error exponent, also referred to as Burnashev's reliability function

$$E(R) := \lim_{\epsilon \rightarrow 0} \frac{-\log \epsilon}{E[\tau_n^*]} = C_1 \left(1 - \frac{R}{C}\right) \quad (1)$$

where C denotes the capacity of the channel, $R \in [0, C]$ is the expected rate of the code, and C_1 is the maximum Kullback-Leibler (KL) divergence between the conditional output distributions given any two inputs. Burnashev proved the upper bound using a two-phase coding scheme. In the first phase, referred to as the *communication* phase, the transmitter tries to increase the decoder's belief about the true message. At the end of this phase, the message with the highest posterior probability is selected as a candidate. The second phase, referred to as the *confirmation* phase, serves to verify the correctness of the output of phase one. Subsequently, in [2] and [3] alternative two-phase coding schemes attaining Burnashev's reliability function were provided, while it was shown in [4] that Burnashev's communication phase can be replaced with any capacity achieving block code. In [5], Burnashev's reliability function was shown to be attainable using a two-phase scheme for a binary symmetric channel (BSC) with an unknown crossover probability. In [6], Burnashev's reliability function was extended to the cost constrained case, and the achievability was proved via a two-phase coding scheme generalizing that of [2]. In [7]–[9], a one-phase scheme for transmission over a DMC with noiseless feedback was proposed. This scheme, first in [7]–[9], is briefly explained next. Each message is subdivided into intervals of size $\frac{1}{M}$ of the unit interval, and given the channel output, the intervals are updated. In the next interval, the true message's median, or 1 if the message's

Finally, a non-asymptotic bound

Remark 4: By Theorem 1 and Proposition 2,

$$\mathbb{E}_{\Gamma^{\text{MaxEJS}}}[\tilde{\tau}_\epsilon] \leq \frac{\log M + \log \log \frac{M}{\epsilon}}{C} + \frac{\log \frac{1}{\epsilon} + 1}{C_1} + \frac{6(4C_2)^2}{CC_1}, \quad (40)$$

and thus MaxEJS encoding together with the decoding and stopping rules described in (26) and (28) achieves Burnashev's optimal asymptotic performance in (23), see Corollary 1.

“Climbing Mount Posterior”

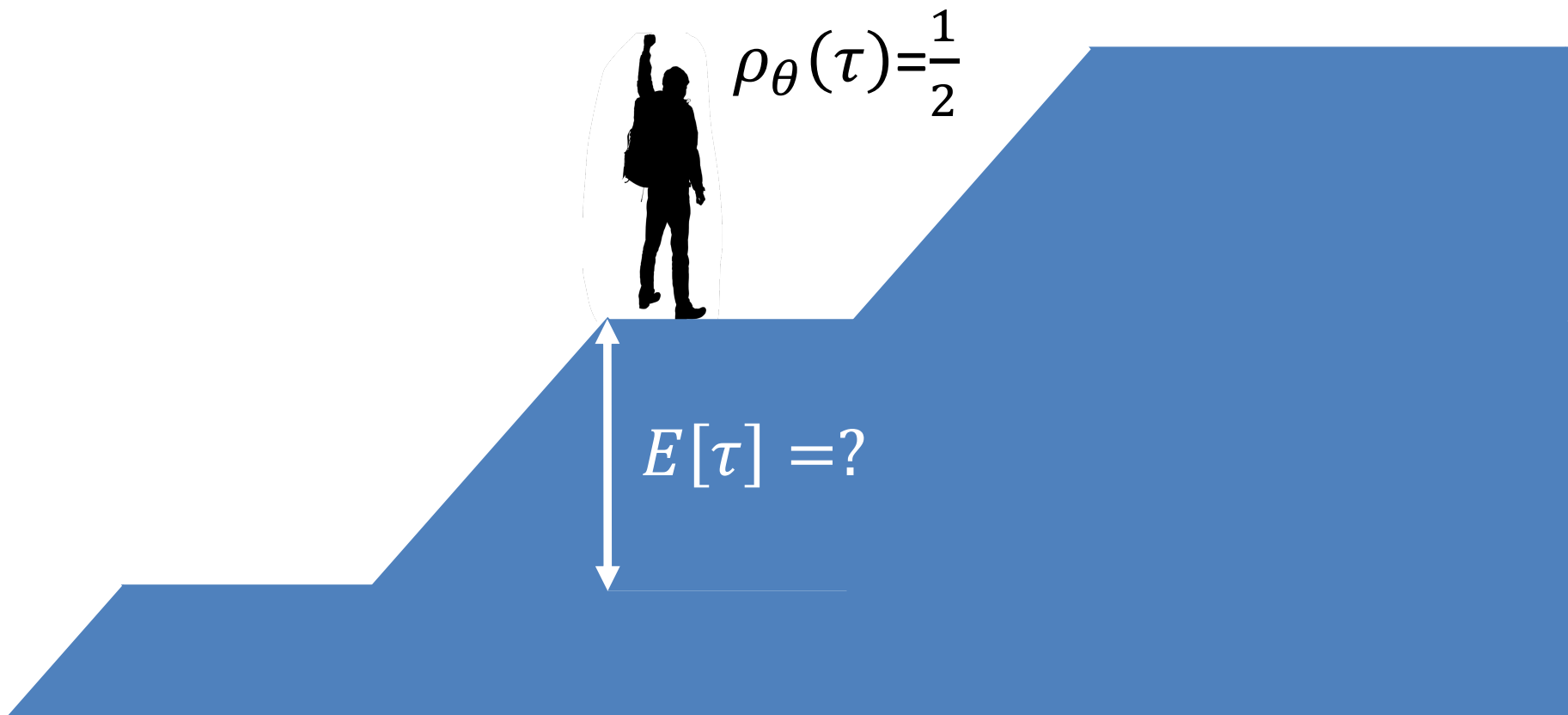


The Journey Begins...

$$\rho_{\theta}(0) = \frac{1}{M}$$



How long to reach the Plateau of $\rho_{\theta}(\tau) = \frac{1}{2}$.

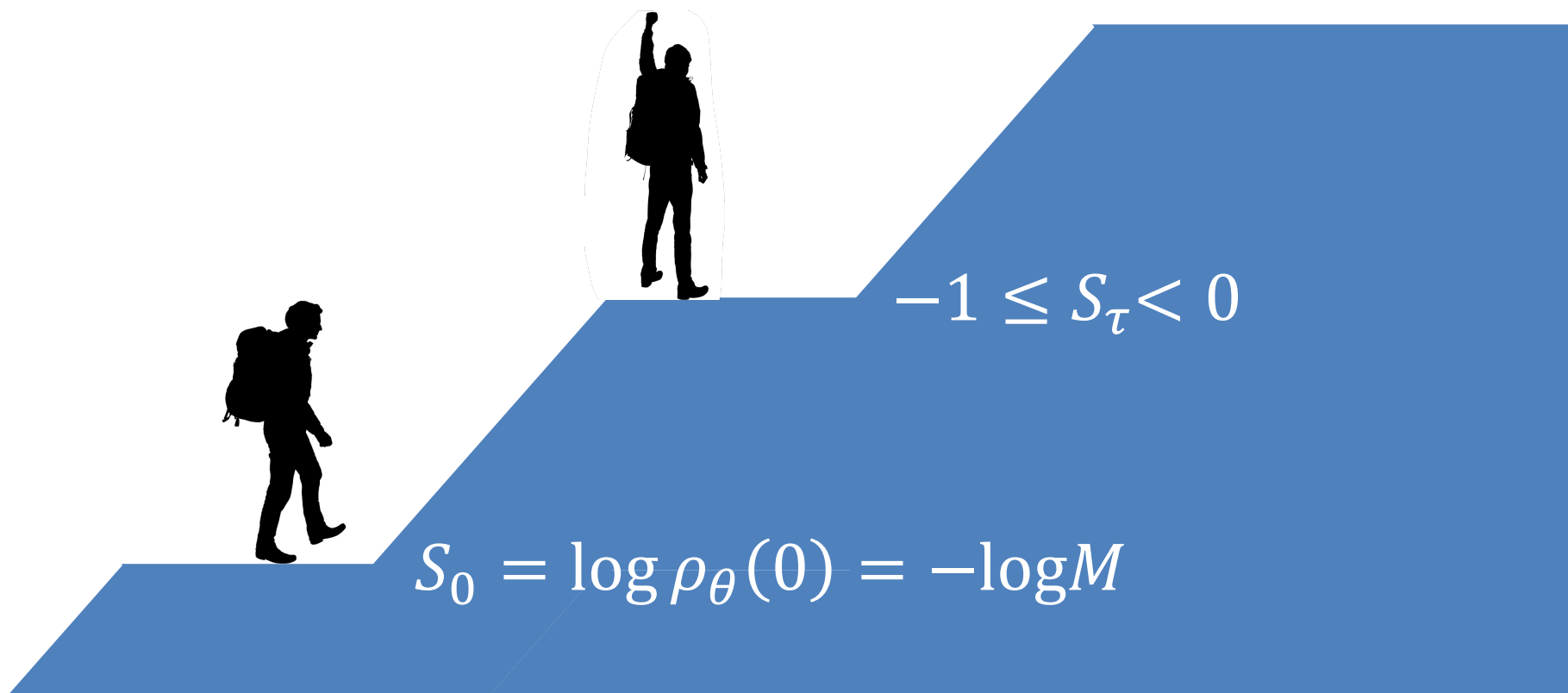


Random walk from $\rho_\theta(0) = \frac{1}{M}$ to $\rho_\theta(\tau) \geq \frac{1}{2}$

ASSUME (FOR NOW) THAT $\pi_0 = \pi_1 = 1/2$

- Define a random walk based on the log of the posterior of the true message:
- $S_n = \log \rho_\theta(n)$
- $S_{n+1} = S_n + X$ where $X = \begin{cases} \log 2q & \text{with probability } q \\ \log 2p & \text{with probability } p \end{cases}$
- Consider the expected value of the step size:
- $EX = p \log 2p + q \log 2q$
- $EX = 1 - H(p)$
- $EX = C$

Random walk from $\rho_\theta(0) = \frac{1}{M}$ **to** $\rho_\theta(\tau) \geq \frac{1}{2}$



Wald's Equality

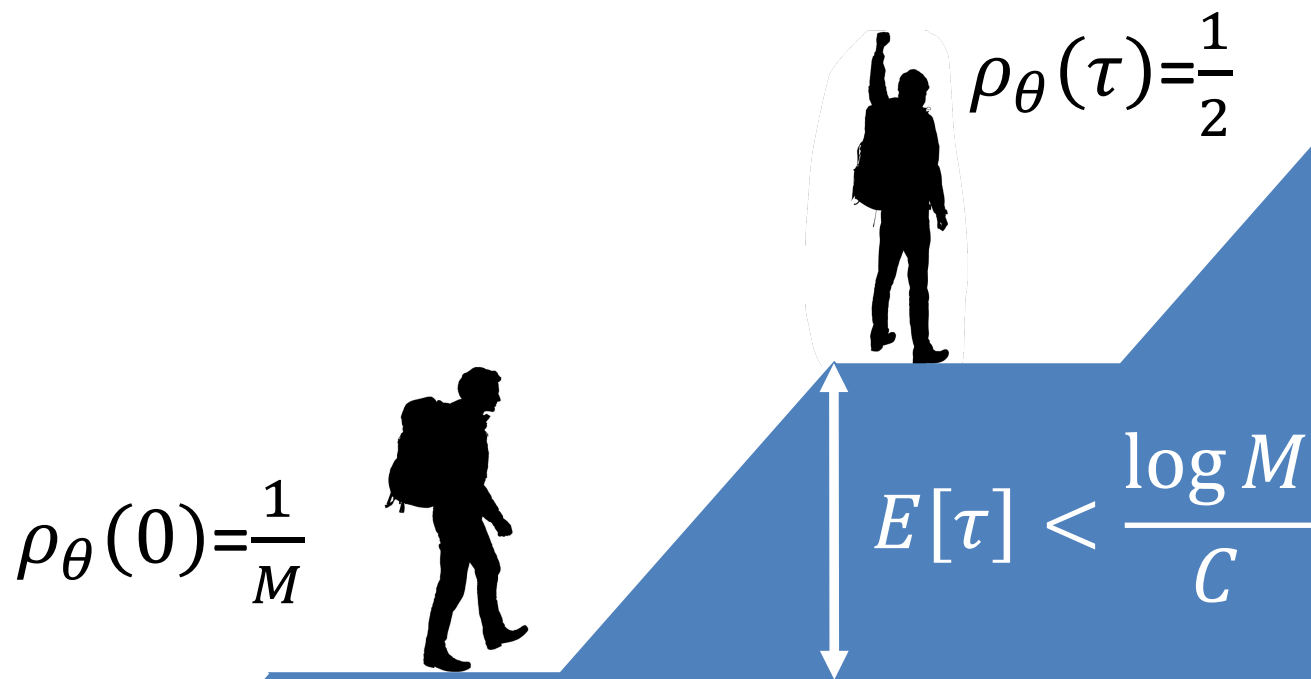
ABRAHAM WALD: $ES_\tau = S_0 + E\tau EX$

- Using Wald's equality:
- $E\tau = \frac{ES_\tau - S_0}{EX}$
- $E\tau < \frac{0 + \log M}{c}$
- $E\tau < \frac{\log M}{c}$



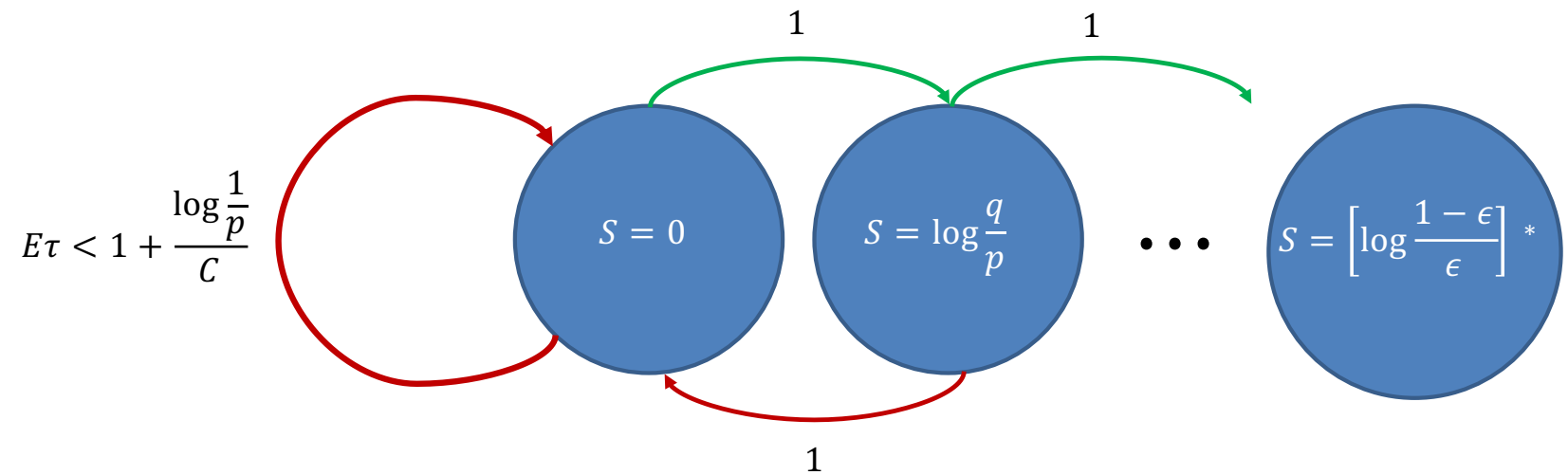
Abraham Wald

Random walk from $\rho_\theta(0)=\frac{1}{M}$ **to** $\rho_\theta(\tau) \geq \frac{1}{2}$

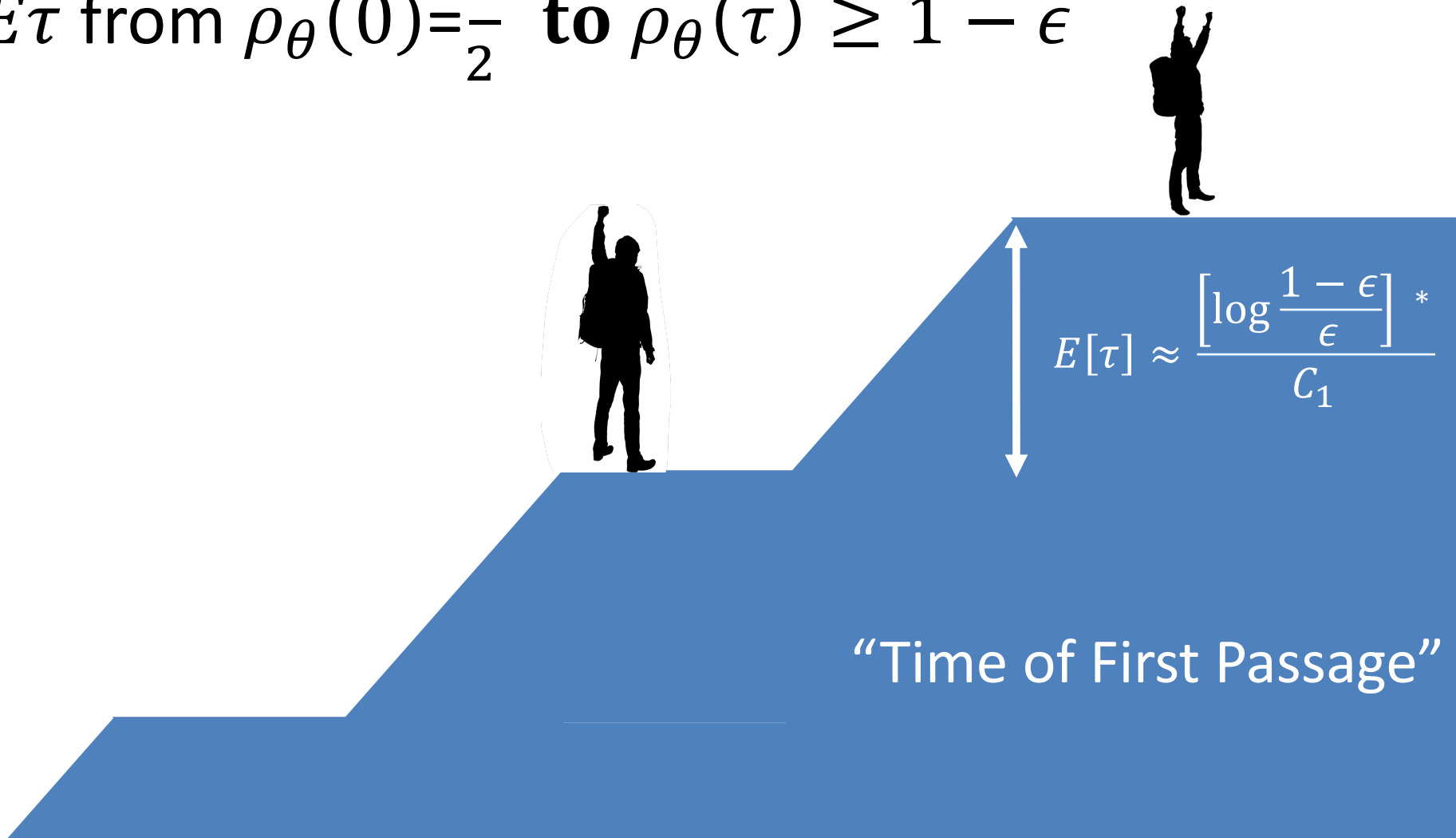


Abraham Wald

A Markov Chain



$E\tau$ from $\rho_\theta(0)=\frac{1}{2}$ **to** $\rho_\theta(\tau) \geq 1 - \epsilon$

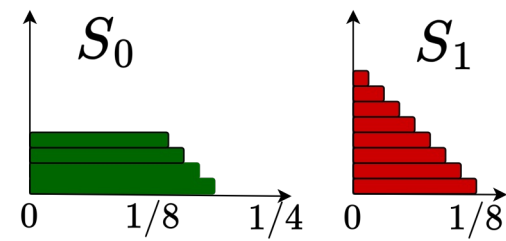
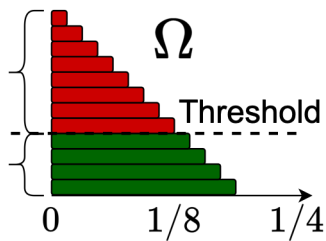


Amaael Antonini: Algorithm and Bounds for BSC

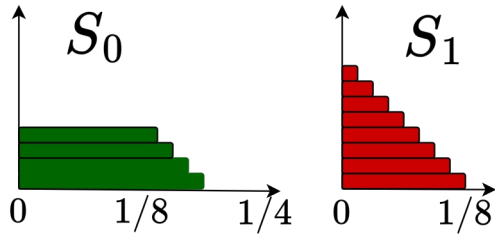


Amaael Antonini

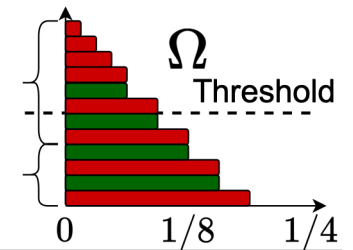
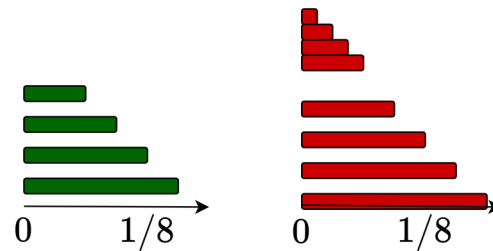
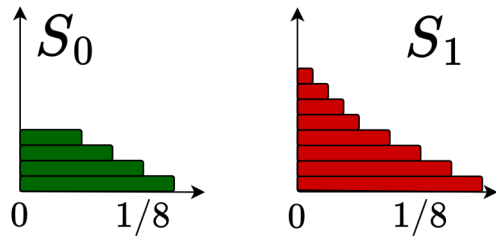
Amaael Antonini's Algorithm



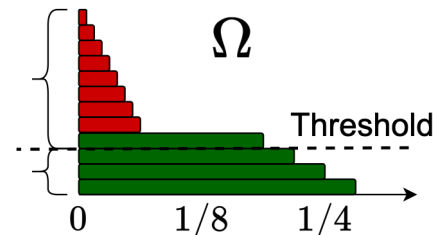
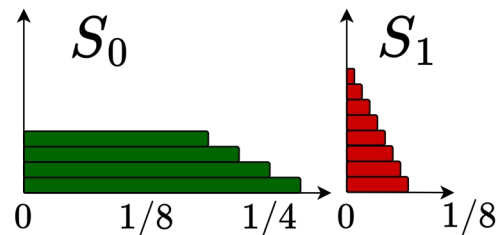
Amaael Antonini's Algorithm



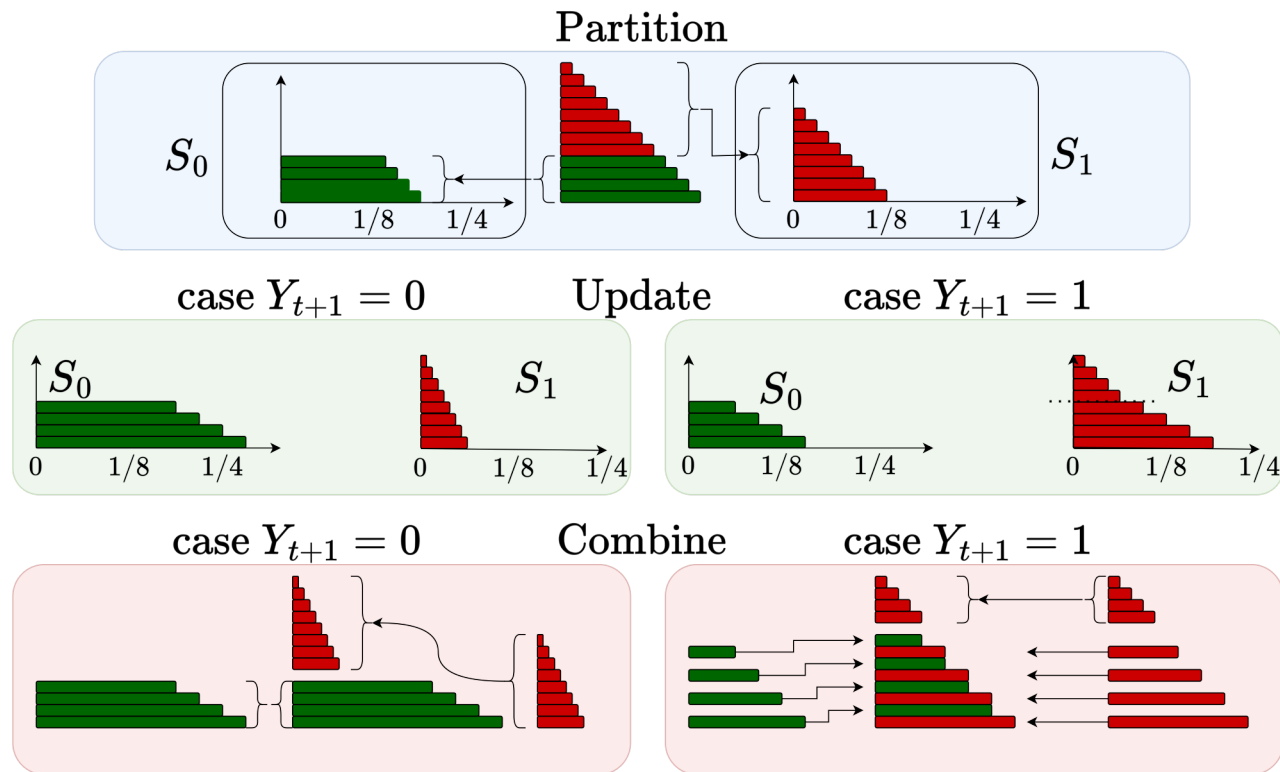
$Y = 1$



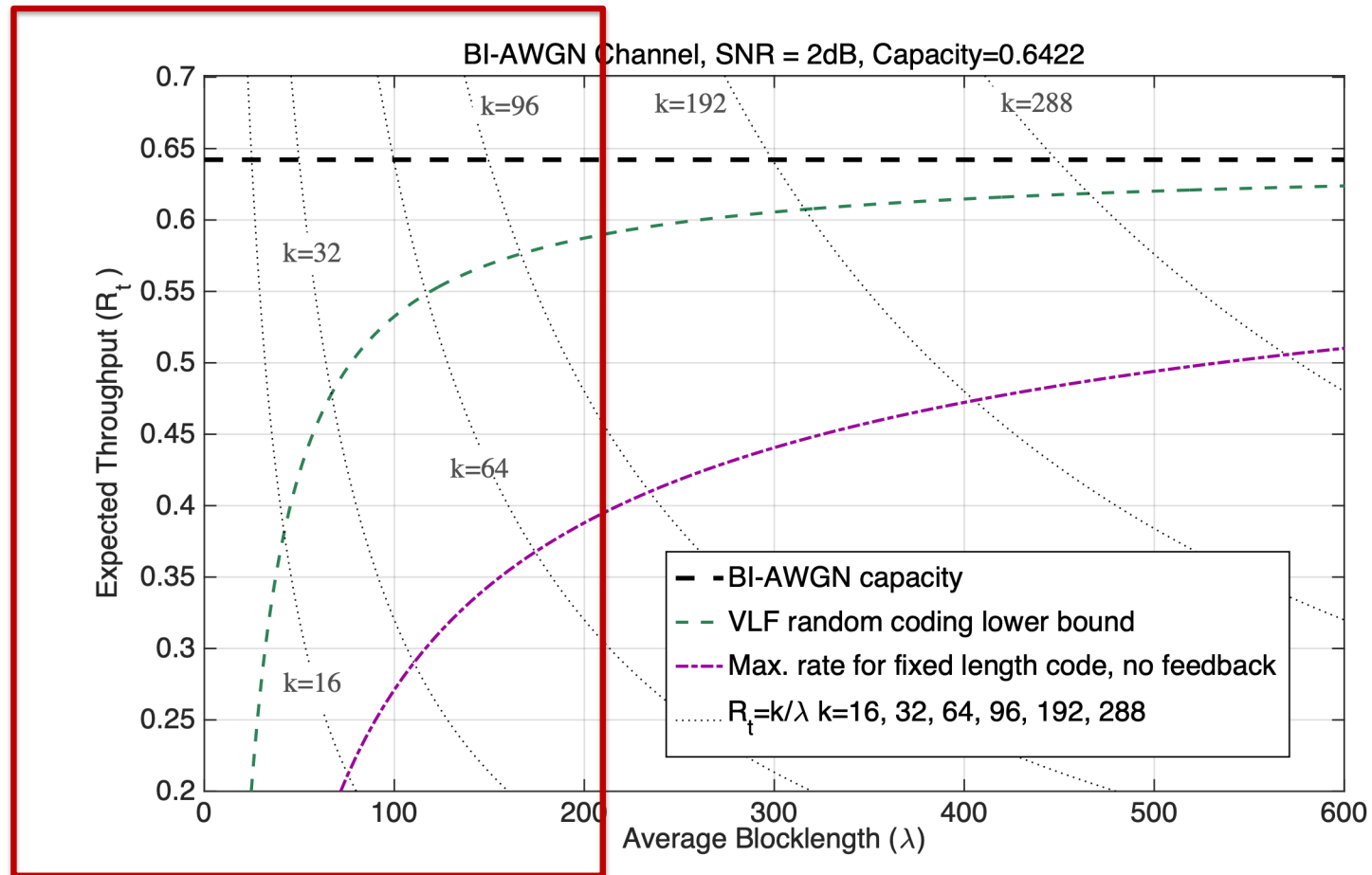
$Y = 0$



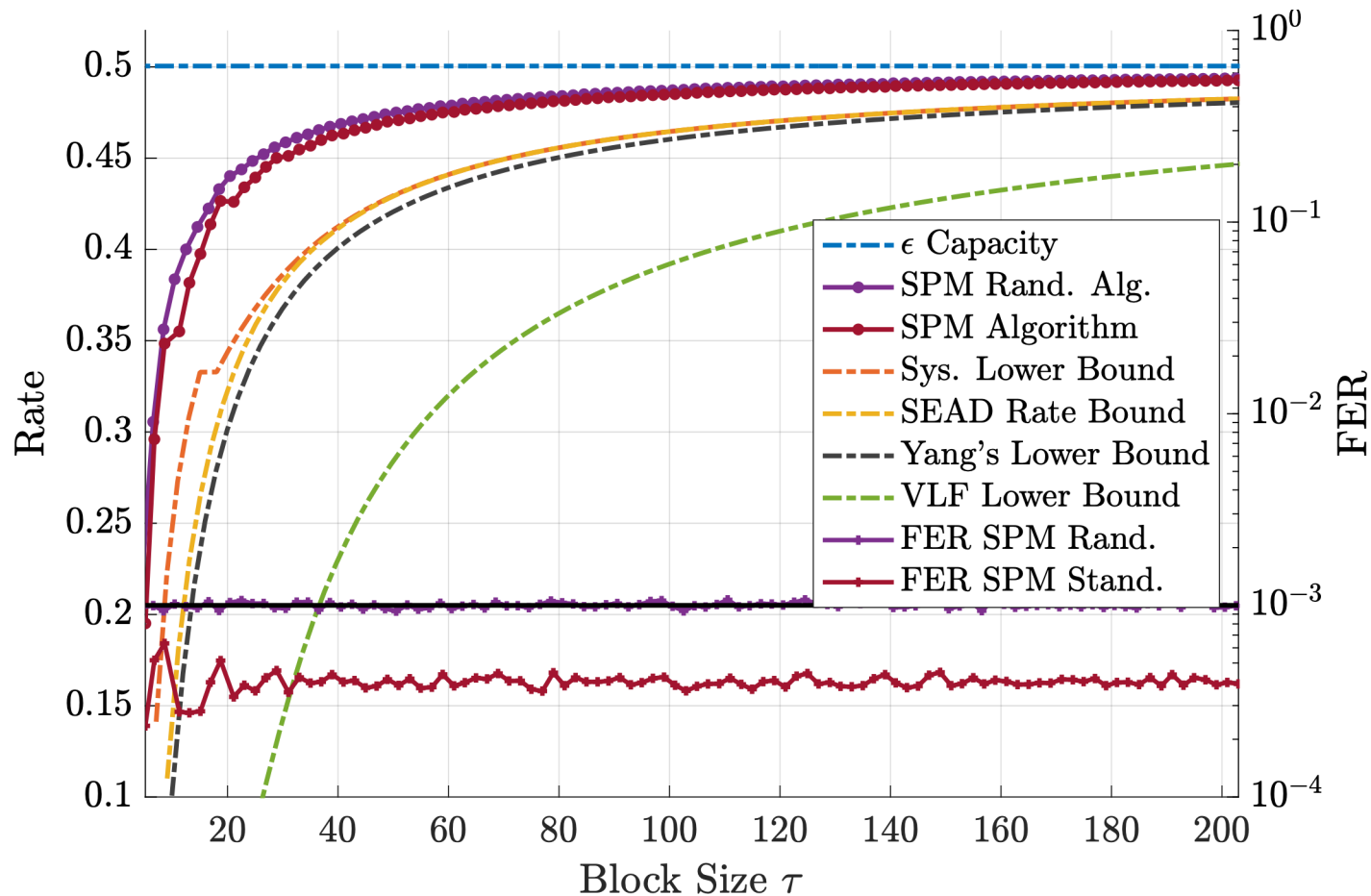
Amaael Antonini's Algorithm



Now we are looking at the first 200 symbols



Amaael Antonini's Bounds and Algorithm



Full Feedback Summary

- Full feedback increases achievable rate by avoiding telling the receiver things that it already knows.
- Capacity can be approached with even 100 channel uses.