

Bayesian Inference with Nonlinear Generative Models

Random Matrices and Random Landscapes

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July 2022



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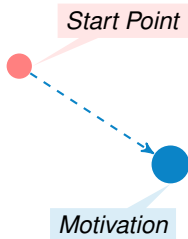


Start Point



Conclusions

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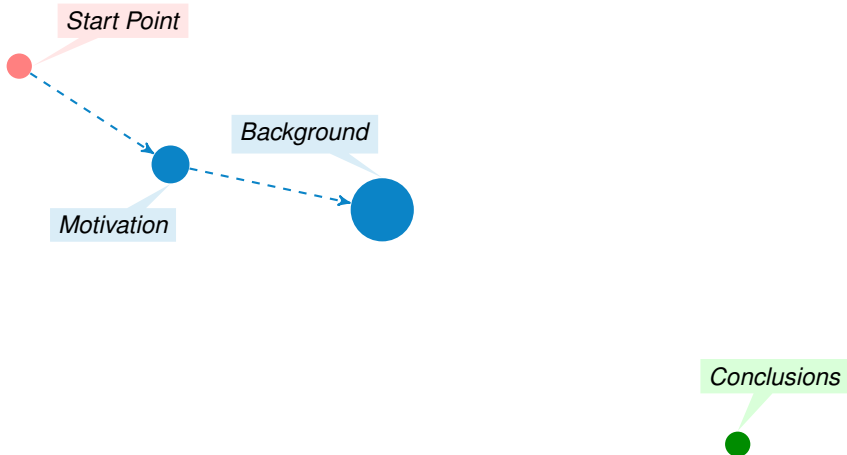
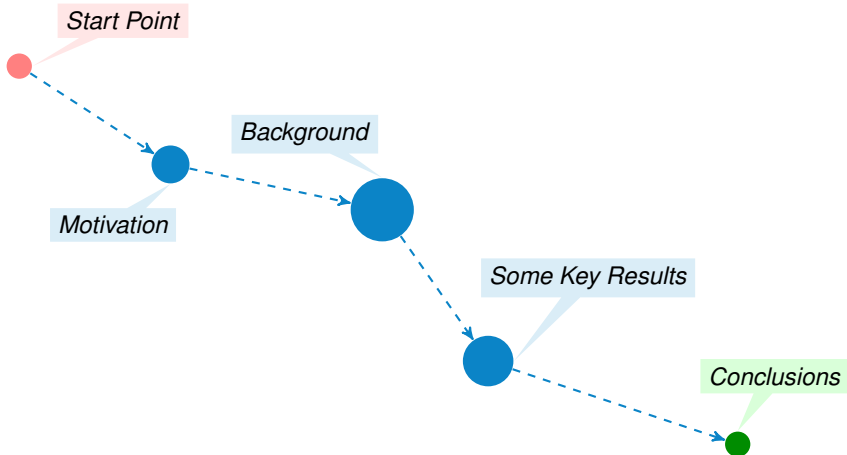


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Understating the Objective



What is the Core Problem?

$\mathbf{s} \in \mathbb{R}^D$ is mapped by $\mathcal{V} : \mathbb{R}^D \mapsto \mathbb{R}^N$

$$\mathbf{x} = \mathcal{V}(\mathbf{s})$$

The mapping is then observed through a noisy channel

$$\mathbf{y} = \mathbf{x} + \mathbf{w}$$

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Ultimate Goal

Recover \mathbf{s} from the *noisy observations*

Mapping via a Gaussian Field

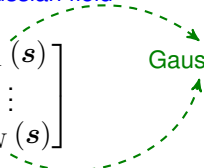
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Gaussian

- The entries of \mathbf{x} are independent zero-mean Gaussians conditioned to \mathbf{s}
- The covariance read

$$\mathbb{E} \{ \mathcal{V}_n(\mathbf{s}_1) \mathcal{V}_n(\mathbf{s}_2) \} = \Phi \left(\frac{\langle \mathbf{s}_1; \mathbf{s}_2 \rangle}{K} \right)$$

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inner product

Mapping via a Gaussian Field

We are used to the *linear* model

Linear model is a **Gaussian field of order one**

$$\mathcal{V}_n(\mathbf{s}) = \langle \mathbf{a}_n; \mathbf{s} \rangle \rightarrow \text{zero-mean Gaussian with variance } 1/K$$

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We are used to the *linear* model  literature of information theory

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But one can in general think of higher-order fields

Example: A purely **quadratic** field

$$\mathcal{V}_n(\mathbf{s}) = \langle \mathbf{s}; \mathbf{J}_n \mathbf{s} \rangle \rightarrow \text{zero-mean Gaussian with variance } 1/K^2$$

whose covariance function is $\Phi(x) = x^2$

Mapping via a Gaussian Field

Why should anyone care about a nonlinear model?

Mapping via a Gaussian Field

Why should anyone care about a nonlinear model?

- ✓ The evidence hidden between the lines of Yan Fyodorov's work says that

Nonlinear models have secrecy potentials

Journal of Statistical Physics (2019) 175:789–818
<https://doi.org/10.1007/s10955-018-02217-9>



A Spin Glass Model for Reconstructing Nonlinearly Encrypted Signals Corrupted by Noise

Yan V. Fyodorov¹ 

Received: 12 August 2018 / Accepted: 11 December 2018 / Published online: 12 January 2019
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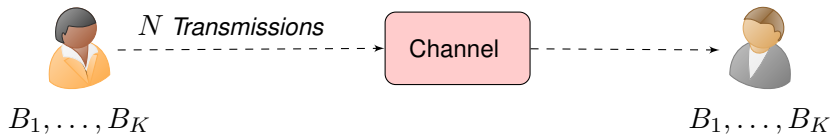
To understand this motivation, we need to take a quick look on

- Secure transmission over the wiretap channel
- Fyodorov's key observation

The Wiretap Channel



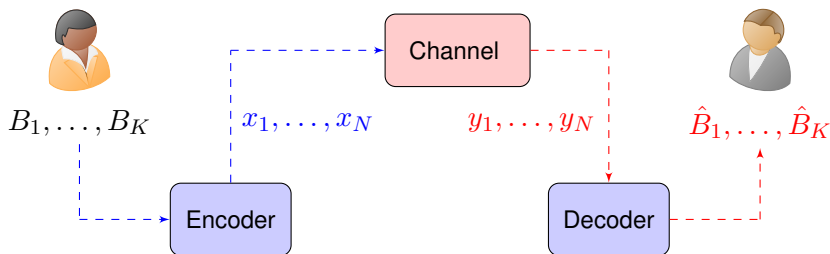
Review: Channel Coding



Transmission rate is

$$R = \frac{K}{N}$$

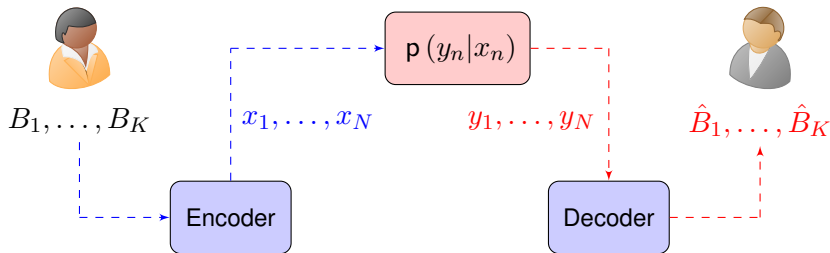
Review: Channel Coding



We desire to have **reliability**, i.e., with fixed rate $R = K/N$

$$\Pr \left\{ (\hat{B}_1, \dots, \hat{B}_K) \neq (B_1, \dots, B_K) \right\} \rightarrow 0 \quad \text{when } N \rightarrow \infty$$

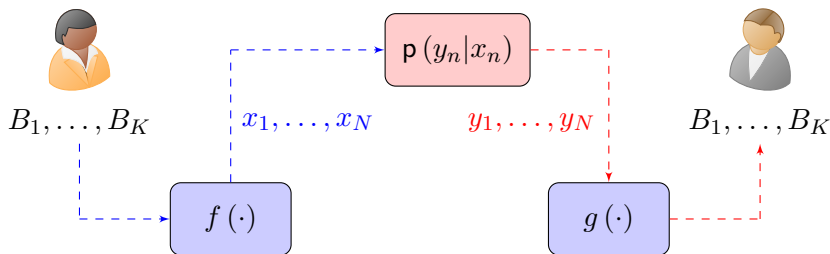
Review: Channel Coding



How we model the channel? **By a conditional distribution**

$$y_n \sim p(y_n | x_n)$$

Review: Shannon's Answer (1948)

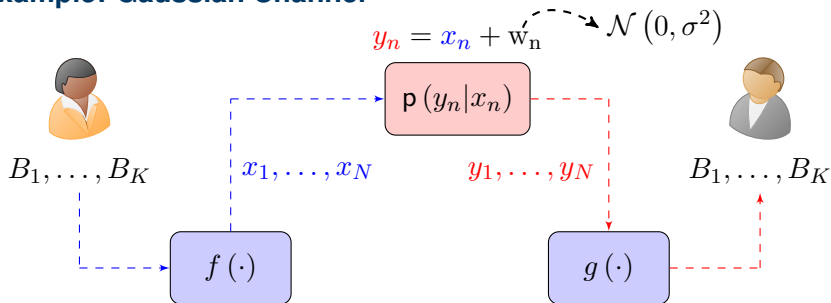


Channel Coding Theorem

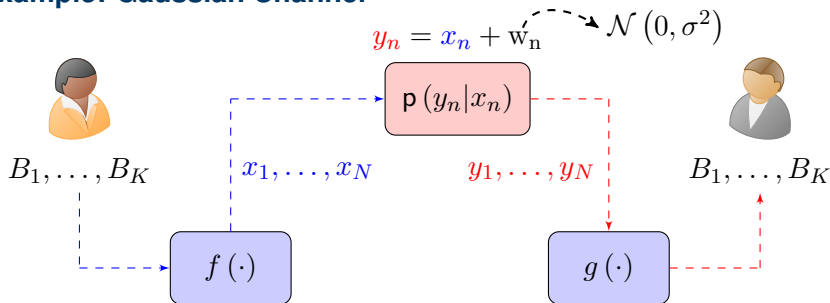
The maximum transmission rate for **reliable** communication is

$$C = \max_{p(x)} I(X; Y) = \max_{p(x)} [H(X) - H(X|Y)]$$

Example: Gaussian Channel



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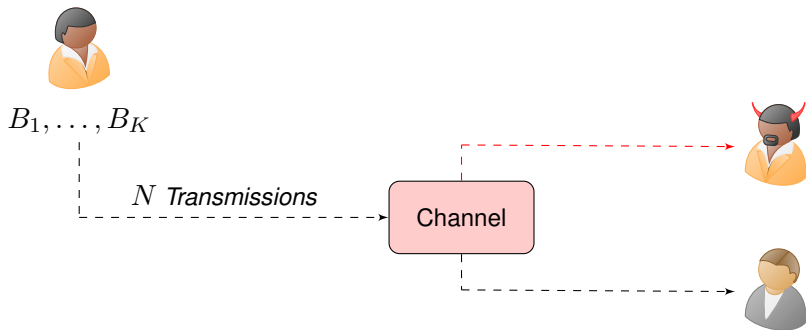


Channel Coding Theorem

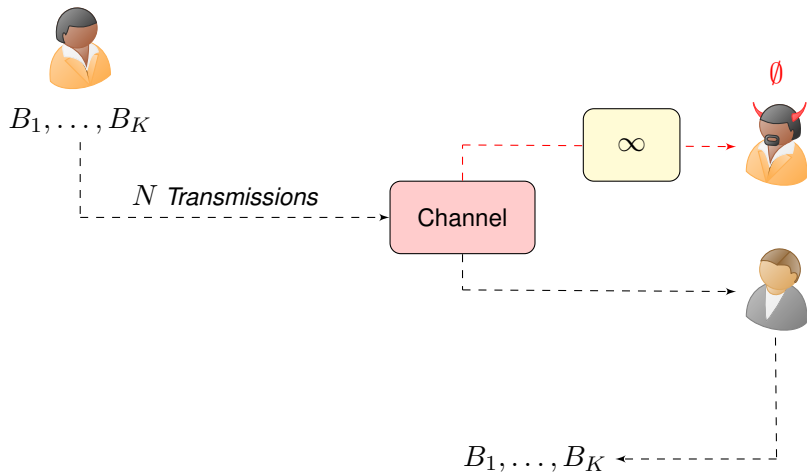
The capacity of the Gaussian channel is given by Gaussian input

$$C = \frac{1}{2} \log \left(1 + \frac{1}{\sigma^2} \right)$$

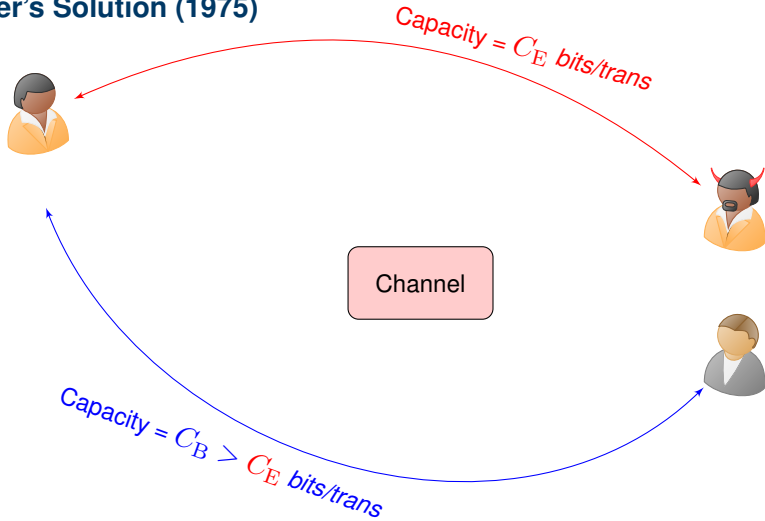
Secure Channel Coding



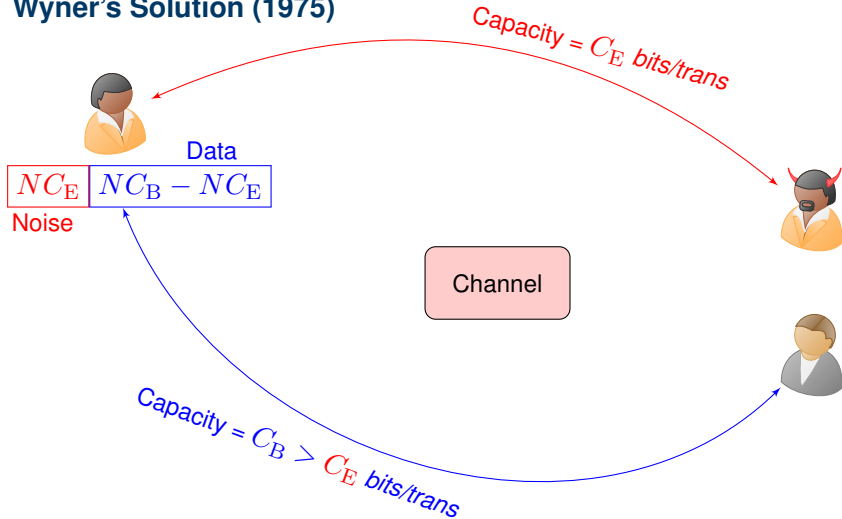
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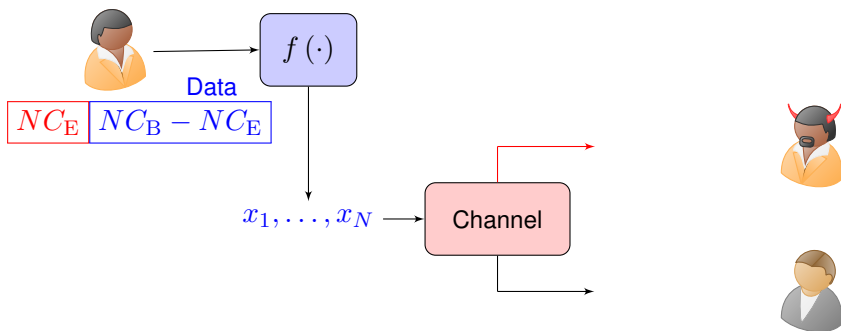
Wyner's Solution (1975)



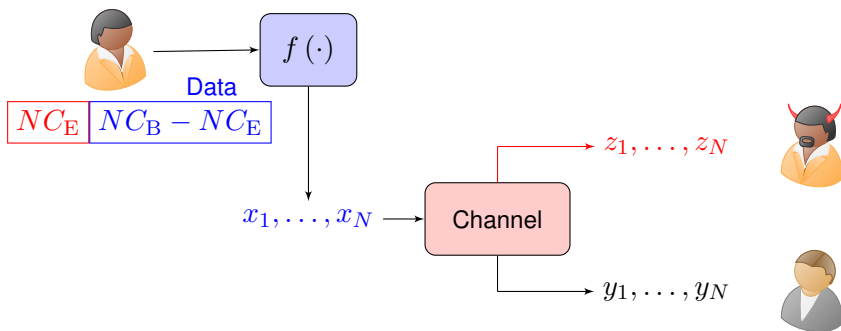
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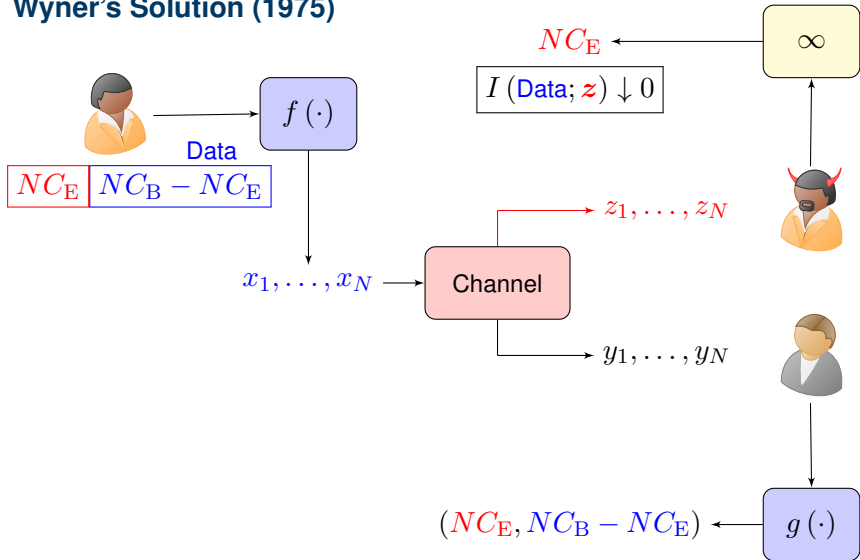
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$$C_{\text{Secure}} = \max_{p(x)} [I(X; Y) - I(X; Z)]^+$$

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noise variance to Bob ← - - -

↓
noise variance to Eve

Earlier Result by Fyodorov

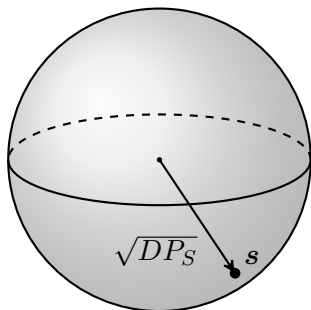


Nonlinear Encryption by Gaussian Fields

Fyodorov uses the nonlinear model to encrypt data on a *hypersphere*

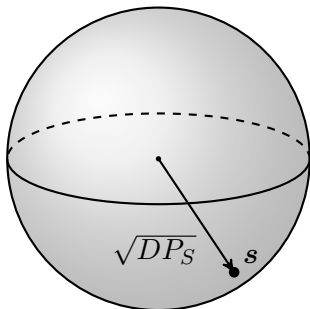
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$$\|s\|^2 = DP_S$$



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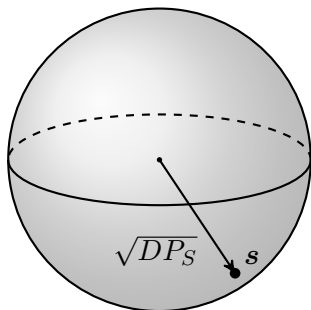
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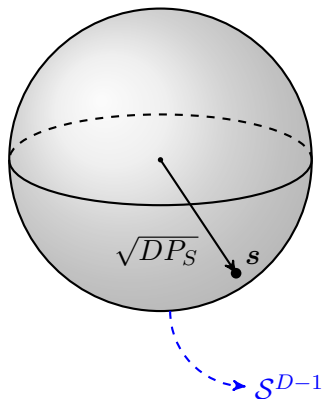
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$$\mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}_N)$$

Nonlinear Encryption by Gaussian Fields

To recover s from \mathbf{y} , Fyodorov uses

- from the **regression** viewpoint “*the method of least-squares*”
- in the **Bayesian framework** “*the maximum-a-posteriori estimator*”

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Main Result: He determines the asymptotic overlap

$$m^* = \lim_{D, N \uparrow \infty} \frac{\mathbb{E} \{ \langle \mathbf{s}; \hat{\mathbf{s}} \rangle \}}{DP_S}$$

with D/N kept fixed via the replica method considering the full-RSB ansatz

Nonlinear Encryption by Gaussian Fields

What does the overlap mean in the wiretap setting?

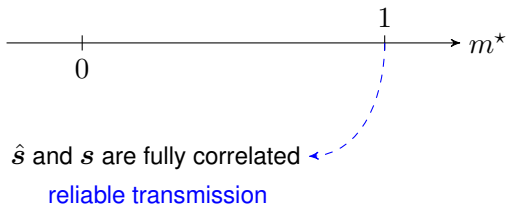
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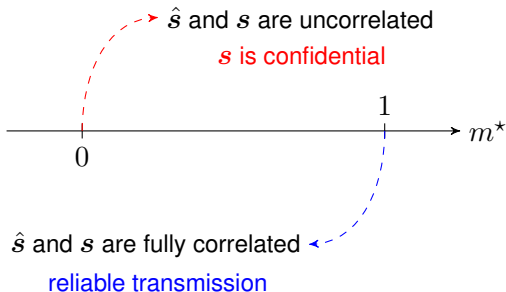
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Key Observations By Fyodorov

Fyodorov reports the following key findings in his paper

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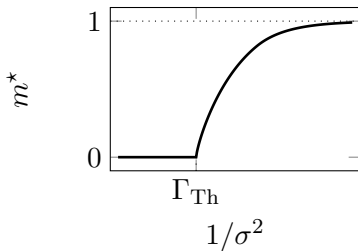
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Example: Purely Quadratic Field



Key Observations By Fyodorov

Fyodorov suggests that this can be used to provide perfect secrecy

The existence of a sharp NSR threshold $\hat{\gamma}_c$ in the pure quadratic encryption case may have useful consequences for security of transmitting the encrypted signal. Indeed, it is a quite common assumption that an eavesdropper may get access to the transmitted signal by a channel with inferior quality, characterized by higher level of noise. This may then result in impossibility for eavesdroppers to reconstruct the quadratically encoded signal even if the encoding algorithm is perfectly known to them.

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Well! This is the wiretap channel of Wyner!

First Try: *Let Fyodorov and Wyner Meet*



Encryption on Top of Sphere Coding

We have two Gaussian channels:

- One to the *good guy Bob* with noise variance σ_B^2
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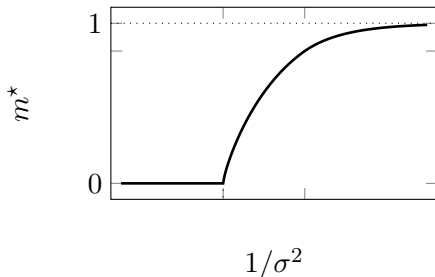
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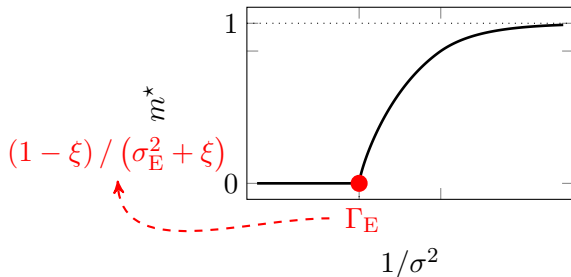


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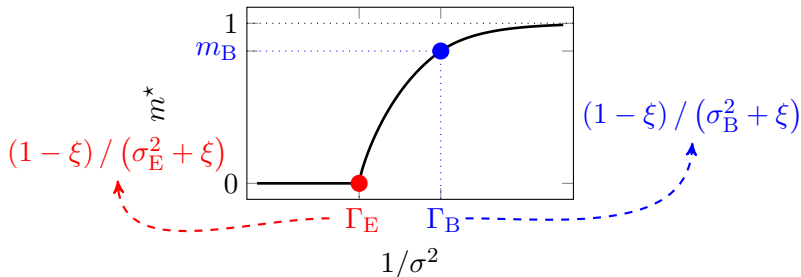


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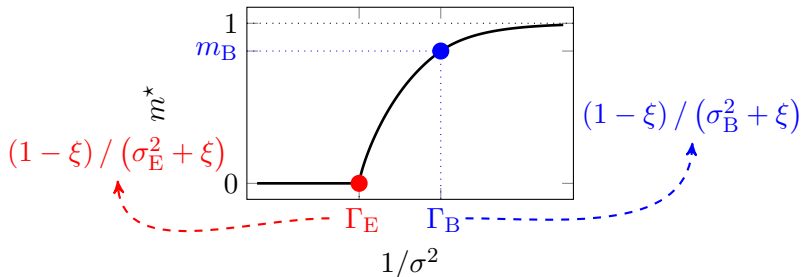


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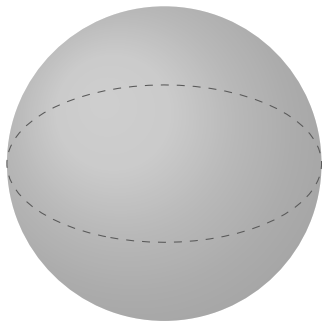


Then, we set the minimum distance $d_B = 1 - m_B$

Encryption on Top of Sphere Coding

We now go on the hypersphere and put 2^K points, such that

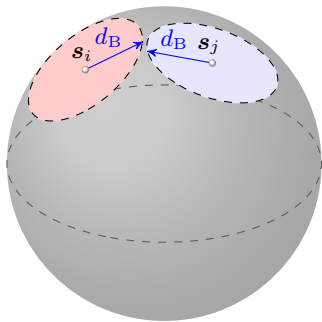
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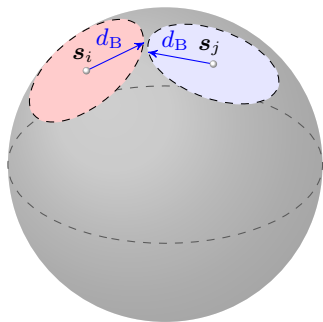
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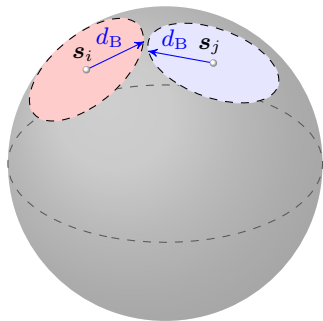
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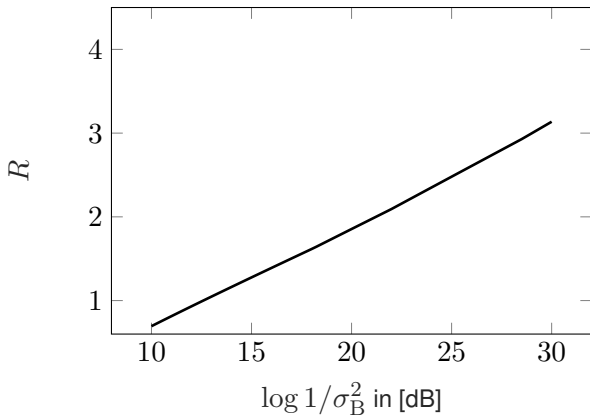
Best thing we can do is to

put as much points as possible

Finding maximum K is sphere covering

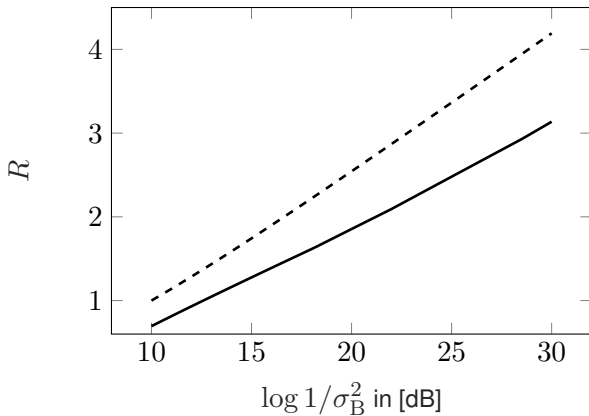
Let's use an optimistic bound

Encryption on Top of Sphere Coding



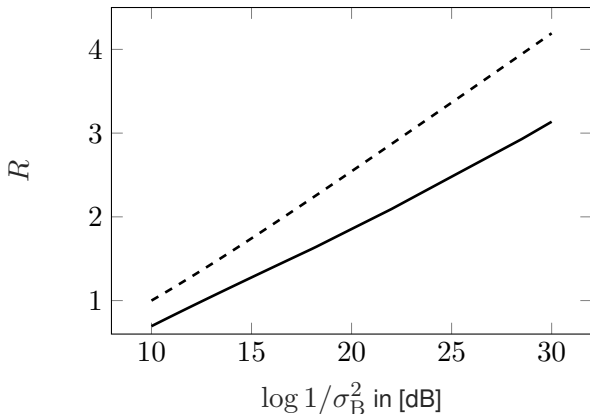
Encryption on Top of Sphere Coding

It didn't really end up well!



Encryption on Top of Sphere Coding

It didn't really end up well! But David MacKay would have told us so



Second Try: Introducing Fyodorov to Wyner



Encoding via Nonlinear Gaussian Fields

We represent the bits via $\mathbf{s} \in \{\pm 1\}^K$ and directly pass them through the field

$$\mathbf{x} = \mathcal{V}(\mathbf{s})$$

At the output of the Gaussian channel, we have

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We then recover \mathbf{s} via the Bayesian optimal algorithm

$$\hat{\mathbf{s}} = \mathbb{E} \{ \mathbf{s} | \mathbf{y} \} = \frac{\mathbb{E}_{\mathbf{s}} \left\{ \mathbf{s} \exp \left\{ -\frac{\|\mathbf{y} - \mathcal{V}(\mathbf{s})\|^2}{2\sigma^2} \right\} \right\}}{\mathbb{E}_{\mathbf{s}} \left\{ \exp \left\{ -\frac{\|\mathbf{y} - \mathcal{V}(\mathbf{s})\|^2}{2\sigma^2} \right\} \right\}}$$

Asymptotics via the Replica Method

We could now do some replica calculations

- Define the variational problem

finding the mutual information \equiv finding a free energy

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RS Solution: Free energy (for you) or mutual information (for me) reads

$$\mathcal{L}_m = \frac{1}{2} \log(1 + \xi_m) + Q_m$$

The overlap m^*

$$m^* = \operatorname{argmin}_{m \in [0,1]} \mathcal{L}_m$$

Asymptotics via the Replica Method

We could now do some replica calculations

- Define the variational problem

finding the mutual information \equiv finding a free energy

- Using the replica method to find the free energy

We focus on the Bayesian optimal case, and hence the RS solution

RS Solution: Free energy (for you) or mutual information (for me) reads

$$\mathcal{L}_m = \frac{1}{2} \log(1 + \xi_m) + Q_m$$

The overlap m^*

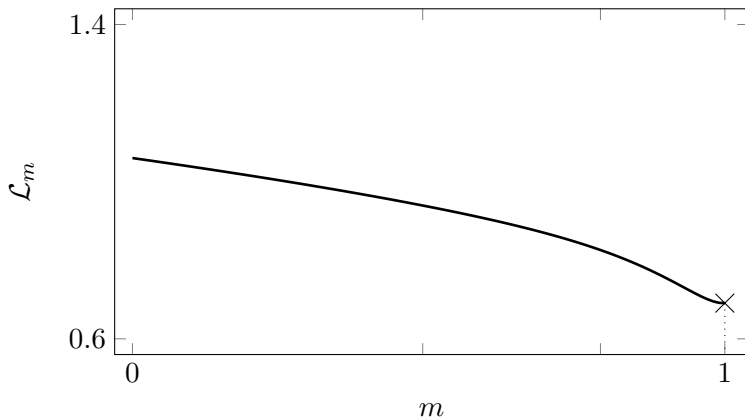
$$m^* = \operatorname{argmin}_{m \in [0,1]} \mathcal{L}_m$$

in terms of $\Phi(\cdot), \dots$

RS Solution: Linear Field

We start with a conventional linear field $\Phi(x) = x$

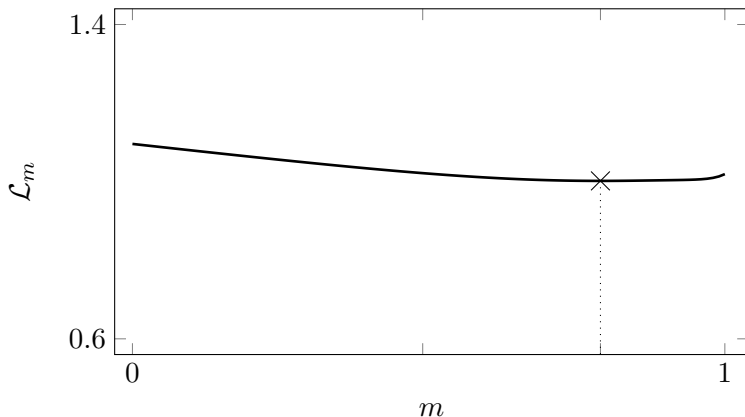
start with small $R = K/N$ and gradually increase it



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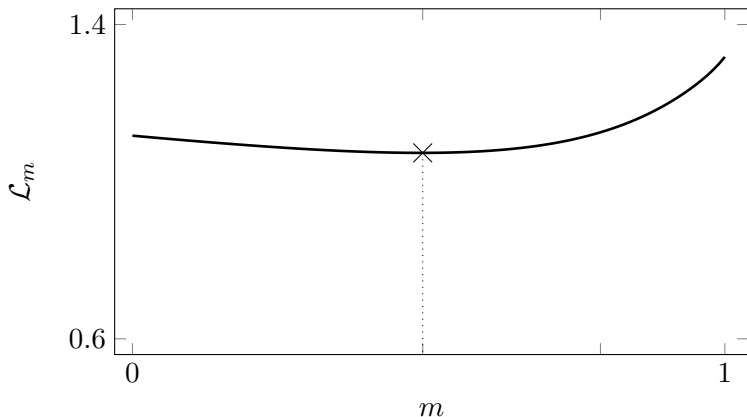
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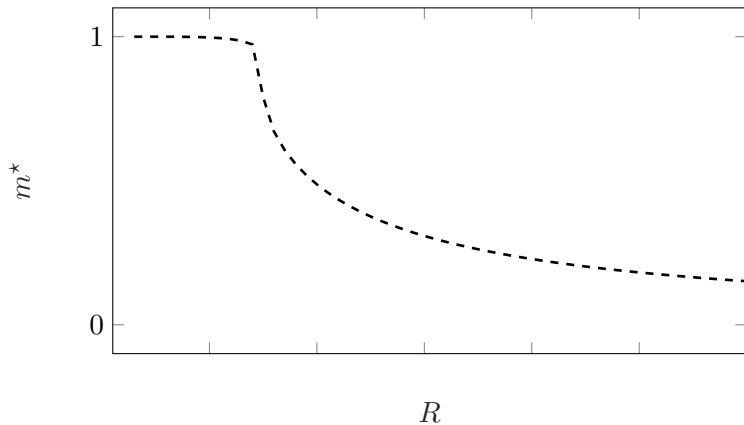
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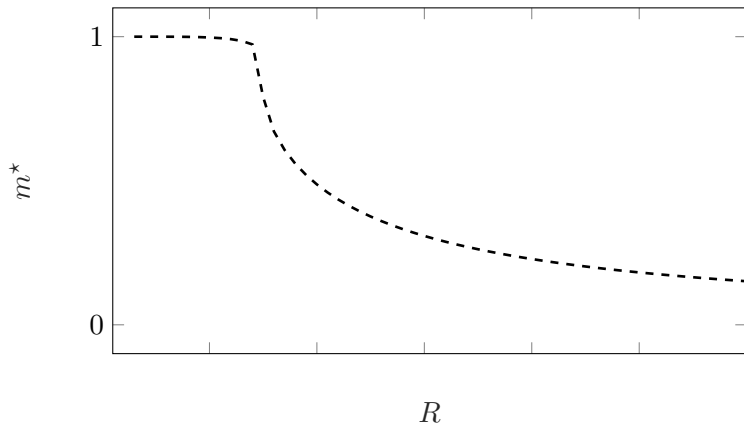
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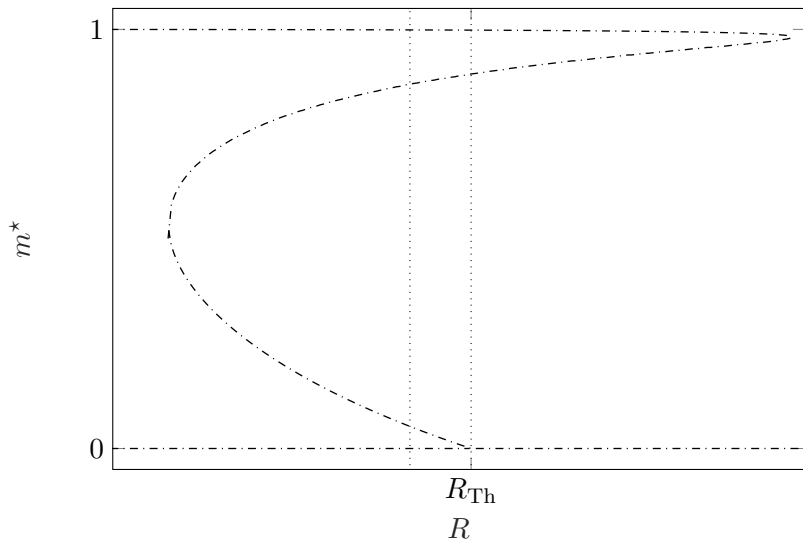
RS Solution: Linear Field



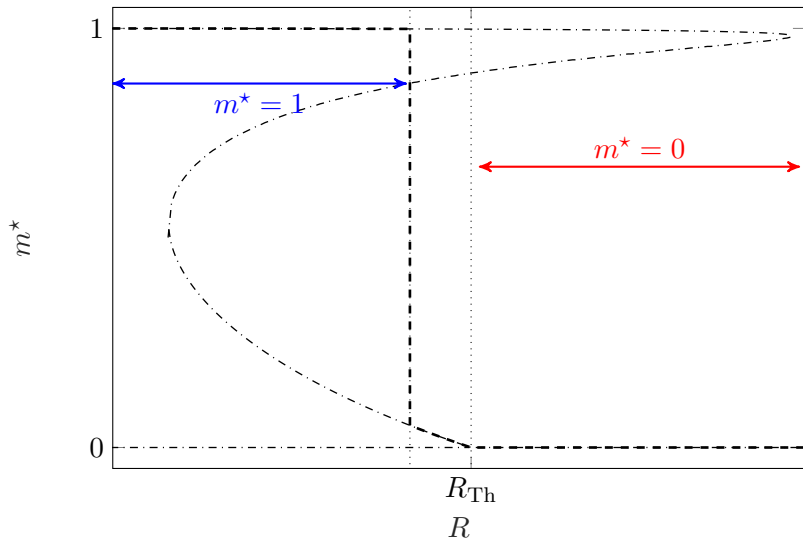
We can easily show that

overlap never touches $m^ = 0$*

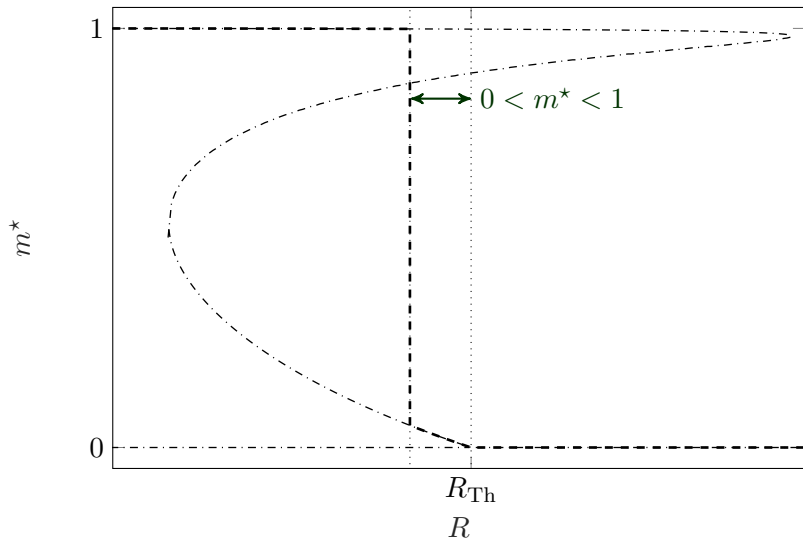
RS Solution: Purely Quadratic Field



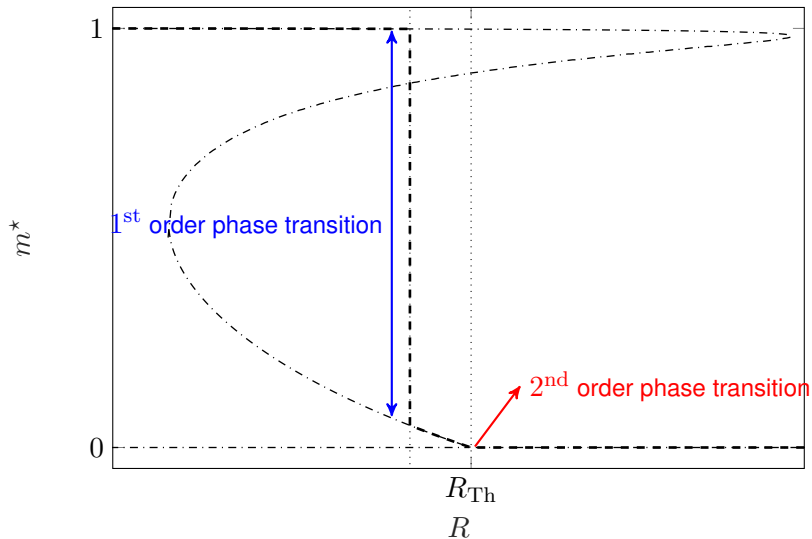
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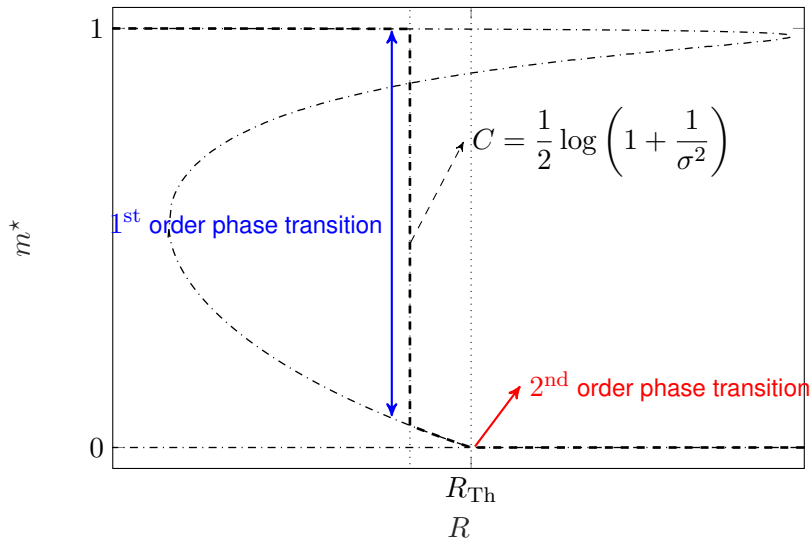
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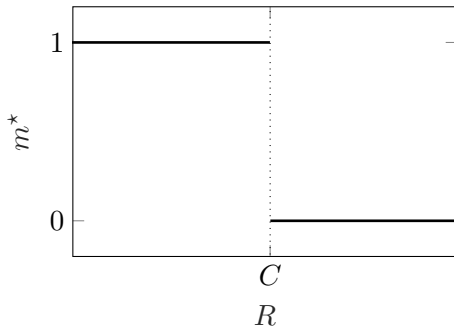


RS Solution: Higher Order Fields

What if we go for higher orders?

RS Solution: Higher Order Fields

What if we go for higher orders?



The moral of story is

- Strictly nonlinear fields show *all-or-nothing* behavior
- The phase transition exactly occurs at Shannon's capacity

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My answer would then be

Yes and No!

A Step Back and Conclusions



Earlier Work by Surlas (1989)

After the initial draft, I found out that Surlas published a paper in 1989

LETTERS TO NATURE

Spin-glass models as error-correcting codes

Nicolas Surlas

Laboratoire de Physique Théorique de l'Ecole Normale Supérieure,
24 rue Lhomond, 75231 Paris Cédex 05, France

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Spin Glasses, Error-Correcting Codes and Finite-Temperature Decoding.

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¹ *Department of Computational Intelligence and Systems Science
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² *The Neural Computing Research Group, Aston University
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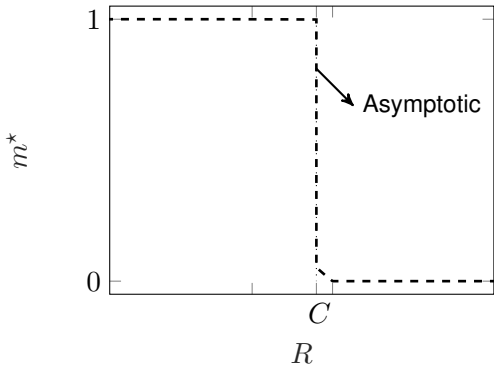
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24 rue Lhomond, 92021 Paris Cedex 05, France

It however did not find its way to information theory literature

as people considered it to be impractical

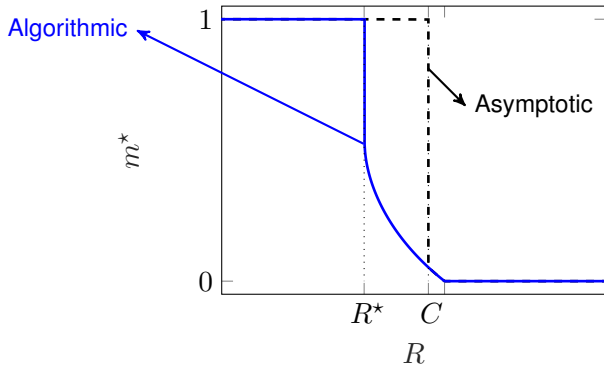
Comments on Practicability

To be honest, “people” were partially right!



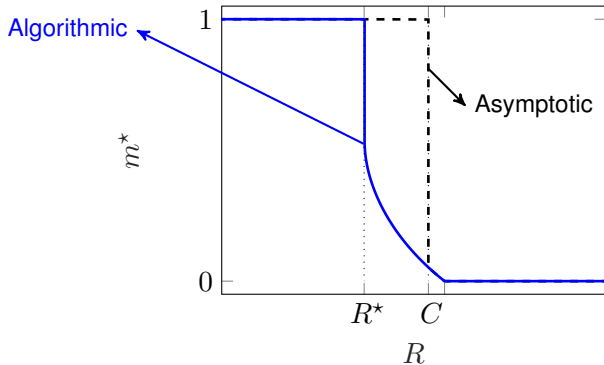
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For higher-order fields, we are always algorithmically at $m = 0$

unless we replace the random field with a spatially-coupled one!

Conclusions

Nonlinear models show *all-or-nothing* property

- It has a direct application to secure coding
- It seems to provide secrecy to other learning problems

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- It has a direct application to secure coding
- It seems to provide secrecy to other learning problems

What am I looking for right now?

- Other applications for nonlinear generative models
- AMP-based implementation of Bayesian inference on nonlinear models

Time for Questions

Special thanks to

- Yan Fyodorov
- Lenka Zdeborová
- Nicolas Macris