

# Error Exponents in Asynchronous Communication

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# Overview of Synchronization

## Multiple levels of synchronization

- Carrier synchronization
  - ▶ PLL, maybe pilot assisted
- Symbol synchronization/timing recovery
  - ▶ Match filter, DLL
- Frame synchronization
  - ▶ Initial/One-shot frame synchronization
  - ▶ Continuous frame synchronization

## Scope of this talk

- Point-to-point communication
- Timing uncertainty in initial frame synchronization

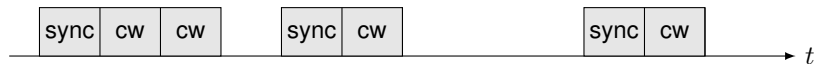
## Two communication scenarios

### Traditional



- Cost of synchronization: low, due to **amortization**

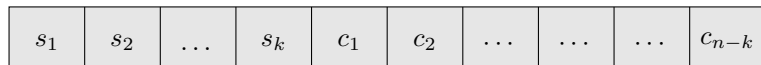
### Emerging



- Examples: sensor networks, etc.
- Cost of synchronization: **high**, as amortization is insignificant

# Separate vs. joint synchronization and coding

## Separate synchronization and coding



symbols for synchronization

symbols for information

## Joint synchronization and coding



symbols for *both* synchronization and information

## Question

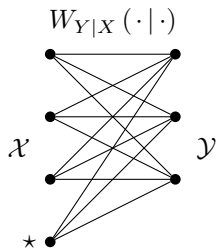
What is the **performance loss** of **separate** synchronization and coding, comparing to **optimal joint** synchronization and coding?

# Asynchronous channel model

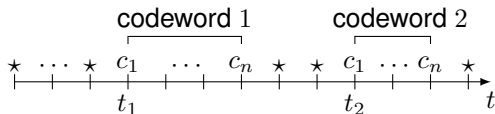
## Asynchronous DMC $(\mathcal{X}, \star, \mathcal{Y}, W)$

- First proposed in [1]
- DMC with a special symbol  $\star$ 
  - ▶ input symbol when **nothing is sent**.
  - ▶ models the effect of noise at channel output

## Channel



- Tx sends codewords at time  $t_1, t_2, \dots$

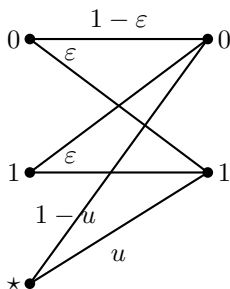


# Asynchronous channel model

## Examples

### Asynchronous BSC

- crossover probability  $\varepsilon$
- $W(\cdot | \star) = \text{Bernoulli}(u)$ .



### Asynchronous AWGN Channel

$$Y^n = \begin{cases} X^n + Z^n & \text{TX transmits} \\ Z^n & \text{TX silent} \end{cases}$$

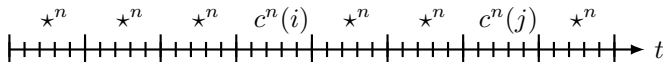
- $X^n$ : average signal power  $P$
- $Z^n$ : average noise power 1
- $W(\cdot | \star) = \text{N}(0, 1)$

# Asynchronous channel model

## Slotted channel assumption

Each slot has length  $n$ , and contains

- either a noise sequence  $\star^n$ ,
- or a codeword sequence
- example:



# Receiver in asynchronous communication

In each time slot, received channel output  $y^n$



$H_0$ : induced by noise sequence  $\star^n$       vs.       $H_1$ : induced by some codeword  $x^n(m)$

A binary (composite) hypothesis testing problem

Channel code  $\mathcal{C} = \{x^n(m) | m = 1, 2, \dots, M = e^{nR}\}$ ,

$$\begin{cases} H_0 : Y_i \stackrel{i.i.d.}{\sim} W(\cdot | \star) \\ H_1 : Y^n \sim W^n(\cdot | x^n(m)) \quad m \in \{1, 2, \dots, M\} \end{cases}$$

## Error events

- **Miss**: detect codeword as noise
- **False alarm**: detect noise as codeword
- **Decoding error**: decode into the wrong codeword



# Performance metrics in asynchronous communication

## Performance metrics

- Rate  $R$
- Miss probability:  $P_m$
- False alarm probability:  $P_f$
- Decoding error probability:  $P_d$
- Error exponents:  $E_m, E_f, E_d$

$$P \approx \exp(-nE)$$

$$n \approx -\frac{1}{E} \log P$$

## Central questions

For an asynchronous DMC  $(\mathcal{X}, \star, \mathcal{Y}, W)$ ,

- What are the fundamental tradeoffs between  $E_m$  and  $E_f$ , given  $P_m, P_f, P_d \rightarrow 0$ ?
  - ▶ Part I of the talk
- How do these tradeoffs compared with those obtained from the **separate synchronization and coding** approach?
  - ▶ Part II of the talk

# Part I:

# Fundamental Tradeoffs

# Regimes of interest

## General scenario

Given rate  $R$ ,  $P_m, P_f, P_d \rightarrow 0$  as  $n \rightarrow \infty$ ,

- Find the trade-off between  $E_m$  and  $E_f$
- Similar to the **Neyman-Pearson** setup, but the objects of interest are **error exponents**.
- Results:
  - ▶ achievability schemes for DMC and AWGN channels: **constant composition code**
  - ▶ (multi-letter) outer bound for DMC

## Special case

Given  $P_m \rightarrow 0$  ( $E_m = 0$ ), what is the optimal  $E_f$ ?

- **Motivation**: communication really **sparse**
- ✓ Complete characterization  $E_f(R)$
- focus of this talk

Optimal  $E_f$  with  $P_m \rightarrow 0$

## Main theorem

Define

$$P_Y(\cdot) \triangleq \sum_x W(\cdot | x) P_X(x)$$
$$W_\star \triangleq W(\cdot | \star),$$

then

$$E_f(R) = \max_{P_X: I(P_X, W) \geq R} D(P_Y \| W_\star) + I(P_X, W) - R$$
$$= \max_{P_X: I(P_X, W) = R} D(P_Y \| W_\star)$$

- **Optimal**  $E_f$  is the **KL-divergence** between
  - ▶ output distribution of the codebook  $P_Y$
  - ▶ output distribution of the  $\star$  symbol  $W_\star$
- The two expressions correspond to two achievability schemes

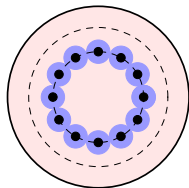
Optimal  $E_f$  with  $P_m \rightarrow 0$

Two achievability schemes

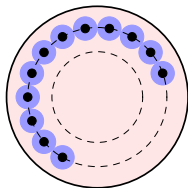
### Joint detection & decoding

- i.i.d. codebook  $P_X$  with  
 $I(P_X, W) \geq R$
- Detect & decode  
**simultaneously** based on **joint**  
**typicality**
- Geometric view:

$$I(P_X, W) = R$$



$$I(P_X, W) > R$$



- More flexible codebook choice

# Optimal $E_f$ with $P_m \rightarrow 0$

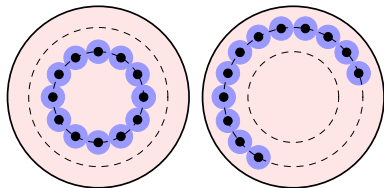
## Two achievability schemes

### Joint detection & decoding

- i.i.d. codebook  $P_X$  with  $I(P_X, W) \geq R$
- Detect & decode **simultaneously** based on **joint typicality**
- Geometric view:

$$I(P_X, W) = R$$

$$I(P_X, W) > R$$



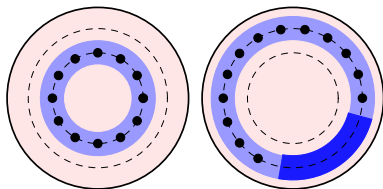
- More flexible codebook choice

### Simpler detection

- i.i.d. codebook  $P_X$  with  $I(P_X, W) = R$
- Detect based on **output distribution**
- Geometric view:

$$I(P_X, W) = R$$

$$I(P_X, W) > R$$



- Simpler detection rule
- Regular decoding afterwards

# Optimal $E_f$ with $P_m \rightarrow 0$

## Example: Asynchronous BSC

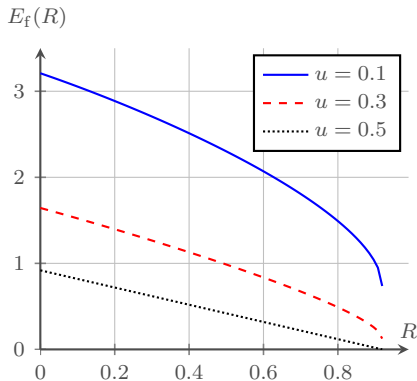
### Optimal $E_f(R)$

$$E_f(R) = D(s \| u)$$

where  $s \geq 0.5$  satisfies

$$H_b(s) - H_b(\varepsilon) = R.$$

BSC with  $\varepsilon = 0.01$



Optimal  $E_f$  with  $P_m \rightarrow 0$

Example: Asynchronous AWGN

Optimal  $E_f(R)$

$$E_f(R) = \text{SNR}/2 - R$$

AWGN with  $\text{SNR} = 10 = 20\text{dB}$

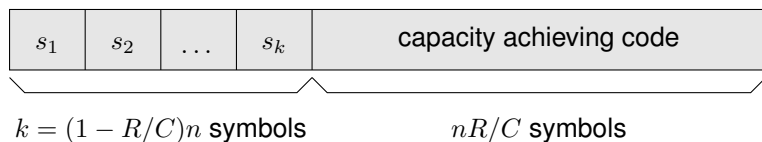


## Part II:

# Suboptimality of Separate Synchronization and Coding

## Separate synchronization and coding (training)

### Training-based scheme (separate synchronization and coding)



- detection algorithm operates on the  $k$  synchronization symbols **only**
- [2] shows training-based schemes achieve **vanishing** false alarm error exponent **at capacity** except for degenerate cases.
- With the slotted model, we quantify the performance loss due to training at **any rate**  $R \in [0, C)$ .

Optimal  $E_f$  with  $P_m \rightarrow 0$

Performance of separate synchronization–coding

Training: best performance

$$E_t(R) = (1 - R/C) D(W(\cdot | s^*) \| W_\star)$$

where  $s^* = \arg \max_{s \in \mathcal{X}} D(W(\cdot | s) \| W_\star)$ .

- standard large deviation argument

Optimal  $E_f$  with  $P_m \rightarrow 0$

Training-based scheme is suboptimal almost everywhere

Training-based scheme is suboptimal almost everywhere

For an asynchronous DMC  $(\mathcal{X}, \star, \mathcal{Y}, W)$  and  $0 < R \leq C$ ,

$$E_t(0) = E_f(0) \text{ and } E_t(R) \leq E_f(R).$$

Furthermore, if the capacity achieving output distribution  $P_Y^*$  satisfies  $D(P_Y^* \| W_\star) > 0$ , then for all  $R > 0$ ,

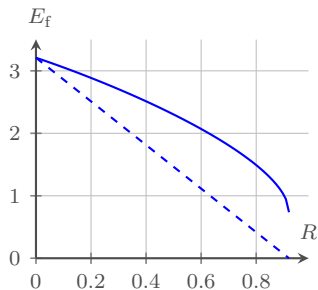
$$E_t(R) < E_f(R).$$

Proof: based on the concavity of  $E_f(R)$ .

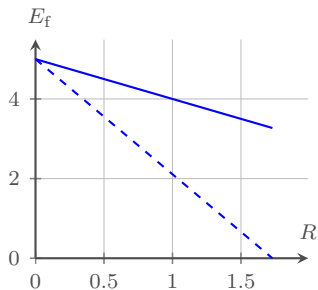
# Training-based scheme is suboptimal almost everywhere

## Example: BSC & AWGN

BSC with  $\varepsilon = 0.01, u = 0.1$



AWGN with SNR=20dB

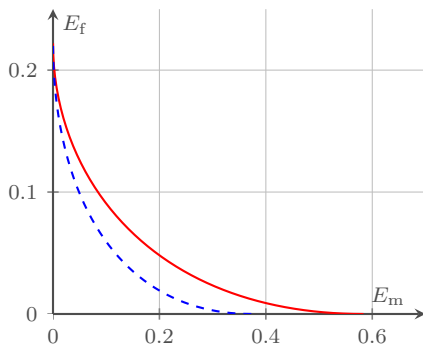


- Larger gap at higher rate
- Smaller difference at lower rate

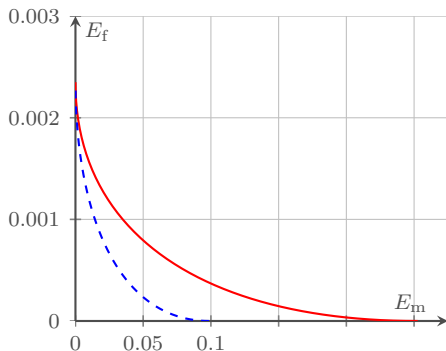
# Trade-off between $E_m$ and $E_f$

Special case: BSC with  $u = 0.5$

$p = 0.80, R = 0.492$  bits



$p = 0.60, R = 0.690$  bits



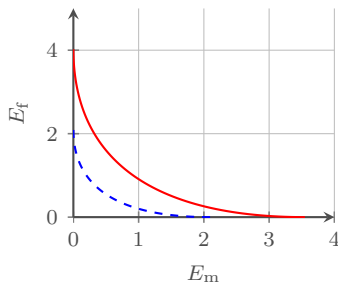
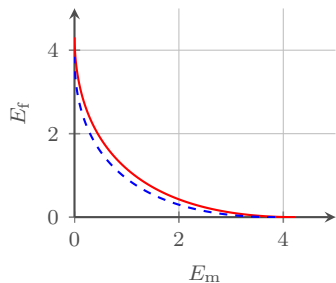
— achievable performance: **joint** sync-coding  
- - - optimal detection: **separate** sync-coding

# Trade-off between $E_m$ and $E_f$

Special case: AWGN with SNR= 20dB

SNR = 20dB, R = 0.5C

SNR = 20dB, R = 0.8C



— achievable performance: **joint** sync-coding  
- - - optimal detection: **separate** sync-coding

# Concluding Remarks

## Insights

- We quantify the suboptimality of training-based schemes
  - ▶ The performance loss is **significant** in the **high rate** regime.
  - ▶ Advanced the insights from [3] .
  
- Coding schemes for joint synchronization and coding
  - ▶ To maximize  $E_f(R)$ , i.i.d.codebook is **sufficient**
    - Typicality decoding, or
    - Detection based on empirical distribution
  - ▶ For tradeoff between  $E_f$  and  $E_m$ , constant composition codebook is better than the i.i.d.codebook.



# Backup slides

# Discussions

## Discussion: slotted vs.unslotted model

$$\text{synchronize} = \underbrace{\text{detect the presence}}_{\text{slotted model}} + \underbrace{\text{locate the position}}_{\text{unslotted model}}$$

### Optimal $E_f$ with $P_m \rightarrow 0$

- [4] shows that, in the **unslotted** model, after detection, using a **prefix** with **sub-linear** length is sufficient to locate the codeword with  $P_m \rightarrow 0$ 
  - ▶ sub-linear length: does not affect the error exponents  $E_f$
  - ▶ prefix design: maximum length shift register sequence
- Results of slotted model **also hold** for the unslotted model!

### Positive $E_m$ requirement

- Stronger requirement for “position location”
- Results for slotted model do **not** hold for the unslotted model.
  - ▶ Only serve as “upper bounds”

# Connection to the Single Message Unequal Error Protection

## Similarities

Single message UEP	Asynchronous Communication
Special codeword	Noise sequence $\star^n$
Regular codewords	Codewords
Miss (special codeword)	False alarm (of noise sequence)
False alarm (of regular codeword)	Miss (a codeword)

## Differences

- In UEP, one can **design** the special codeword
- In asynchronous communication, it is constrained to be **repetition** (of  $\star$ ).

## Asynchronous communication

- can be viewed as UEP with constraint on special message design
- can be extended to obtain results on single message UEP that is more general than [5]

## Future directions

- More complete characterization of the error exponents
- Sequential detection
- Unslotted model

More details

# Detailed analysis

## Acceptance region for codewords: $\mathcal{A}_n$

- If  $y^n \in \mathcal{A}_n$ , we consider the channel input to be a certain codeword  $x^n(m)$
- otherwise we consider the channel input as  $\star^n$ .
- $\mathcal{A}_n$ : the acceptance region for codewords
- $\mathcal{B}_n \triangleq \mathcal{A}_n^c$  to be the rejection region for codewords

## Error probabilities analysis

$$P_m(\mathcal{C}^{(n)}) \triangleq \max_m P_m(m) \quad \triangleq \max_m W^n(\mathcal{A}_n^c | x^n(m))$$

$$P_f(\mathcal{C}^{(n)}) \triangleq W^n(\mathcal{A}_n | \star^n) \quad \triangleq W_{\star}^n(\mathcal{A}_n)$$

$$P_d(\mathcal{C}^{(n)}) \triangleq \max_m P_d(m) \quad \triangleq \max_m \sum_{\hat{m} \neq m} W^n(g_n^{-1}(\hat{m}) | f_n(m))$$

# Scenario 1

Optimal  $E_f$  with  $P_m \rightarrow 0$



Optimal  $E_f$  with  $P_m \rightarrow 0$

Converse

### Main idea

- $P_m \rightarrow 0$  and  $P_d \rightarrow 0$ 
  - ▶ The **acceptance region**  $\mathcal{A}_n$  for codewords **cannot be too small**
  - ▶ Essentially no smaller than the union of each codeword's typical shell
- $P_f$  cannot be too small
  - ▶ as the chance that  $\star^n$  falls into the acceptance region **cannot be too small**

### Technique

- First prove it for **constant composition code**
- Then extends to general code
- Every code has a constant composition subcode with **essentially** the same rate

## Scenario 2

Optimal  $E_m$  with  $P_f \rightarrow 0$

Optimal  $E_m$  with  $P_f \rightarrow 0$

Main results

$$\underline{E}_m(R) \leq E_m(R) \leq \overline{E}_m(R)$$

Lower bound

Let  $\mathcal{V}_\star = \{V : \sum_x P_X(x) V(\cdot | x) = W_\star\}$ ,

$$\underline{E}_m(R) = \max_{P_X: I(P_X, W) \geq R} \min_{V \in \mathcal{V}_\star} D(V \| W | P_X)$$

where  $D(V \| W | P_X) \triangleq \mathbb{E}_{P_X} [D(V(\cdot | X) \| W(\cdot | X))]$ .

Upper bound

$$\overline{E}_m(R) = \max_{P_X: I(P_X, W) \geq R} \mathbb{E}_{P_X} [D(W_\star \| W(\cdot | X))],$$

## Optimal $E_m$ with $P_f \rightarrow 0$

### Achievability scheme

- Constant composition codebook with type  $P_X$
- Rejection region for codewords: typical shell of the noise sequence  $\star^n$
- $V \in \mathcal{V}_\star$ : “confusing” channel realizations
  - ▶ Makes the output type of a codeword same as  $\star^n$

### Upper bound proof idea

- Rate  $R$ : a constraint on the codebook type  $P_X$
- Consider a single codeword  $x^n$  with type  $P_X$  and  $\star^n$
- Swap the role of the two sequences
  - ▶  $x^n$ : “noise sequence”
  - ▶  $\star^n$ : “codeword sequence”
- Apply the result on  $E_f(R)$ , and average over the type  $P_X$

# Scenario 3

Trade-off between

$E_m$  and  $E_f$

## Trade-off between $E_m$ and $E_f$

### Achievability result for DMC

For an asynchronous DMC  $(\mathcal{X}, \star, \mathcal{Y}, W)$ , given a rate  $R$  and a miss error exponent constraint  $e_m$ ,

$$\underline{E}_f(R, e_m) = \max_{P_X: I(P_X, W) \geq R} \min_{V: D(V \| W | P_X) \leq e_m} \left[ D(Q_V \| W_\star) + |I(P_X, V) - R|^+ \right]$$

where  $Q_V(\cdot) = \sum_x P_X(x) V(\cdot | x)$ .

### Achievability

- a code achieves miss error exponent  $e_m$ 
  - ⇒ it also achieves  $P_m \rightarrow 0$  for any  $V$  s.t.  $D(V \| W | P_X) \leq e_m$ 
    - ▶ use the **typical shell** of all these  $V$ s for the detection region of the noise sequence  $\star^n$
- Check:  $e_m = 0 \Leftrightarrow V = W \Rightarrow \underline{E}_f(R, e_m = 0) = E_f(R)$

$$\underline{E}_m(R, e_f)$$

Similarly, given a rate  $R$  and a false alarm error exponent constraint  $e_f$ , the following lower bound for the miss reliability function is achievable via a sequence of constant composition codebooks

$$\underline{E}_m(R, e_f) = \max_{P_X: I(P_X, W) \geq R} \min_{V: D(Q_V \| Q_Y) \leq e_f} D(V \| W | P_X).$$

## Trade-off between $E_m$ and $E_f$

Special case: BSC with  $u = 0.5$

### Joint Synchronization & Coding

$$e_f(\delta) \leq D(\delta \| u)$$

$$e_m(\delta) \leq \min_{\kappa \in [\delta - \bar{p}\varepsilon, \kappa^*]} \left[ \bar{p}D\left(\frac{\delta - \kappa}{\bar{p}} \parallel \varepsilon\right) + pD\left(\frac{\kappa}{p} \parallel \bar{\varepsilon}\right) \right]$$

where  $\bar{x} \triangleq 1 - x$  and  $\kappa^* = \min\{\delta, p(1 - \varepsilon)\}$ .

### Training

$$e_m(\lambda) \leq \left(1 - \frac{R}{C}\right) D(q_\lambda \| \varepsilon)$$

$$e_f(\lambda) \leq \left(1 - \frac{R}{C}\right) D(q_\lambda \| u)$$

where  $q_\lambda \propto \varepsilon^\lambda u^{1-\lambda}$ ,  $\lambda \in [0, 1]$ .



# Trade-off between $E_m$ and $E_f$

## Achievability result for AWGN

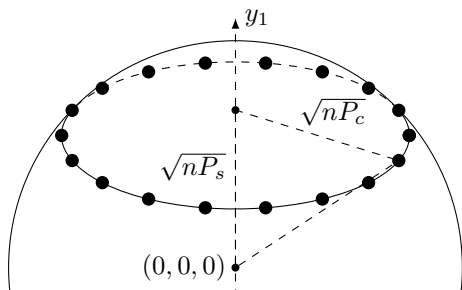
### Code design

Find  $P_c$  and  $P_s$  satisfy

■  $R = \log(1 + P_c)/2$

■  $P_s = P - P_c$

■  $X^n = (\sqrt{nP_s}, \hat{X}_1, \dots, \hat{X}_{n-1})$



### Decision rule

$$\begin{cases} H_0 : & \text{noise} \\ H_1 : & \text{some codeword} \end{cases} \quad \Rightarrow \quad ay_1 + b\|y_2^n\| \underset{\hat{H}=H_0}{\overset{\hat{H}=H_1}{\gtrless}} \sqrt{n\eta}$$

## Trade-off between $E_m$ and $E_f$

Special case: AWGN with SNR= 20dB

### Joint Synchronization & Coding

$$e_f(\eta) \leq \max_{(a,b) \in [0,1]^2} \min_{0 \leq r \leq \eta - b} \left[ \frac{r^2}{2a^2} + I_{\chi_1^2} \left( \frac{(\eta - r)^2}{b^2} \right) \right]$$

$$e_m(\eta) \leq \max_{(a,b) \in [0,1]^2} \min_{\eta - b\sqrt{P_c+1} \leq r \leq \eta} \left[ \frac{(r - a\sqrt{P_s})^2}{2a^2} + I_{\text{SG}} \left( P_c, \frac{(\eta - r)^2}{b^2} \right) \right]$$

where

$$I_{\chi_1^2}(x) \triangleq \frac{1}{2}(x - \ln x - 1)$$

$$I_{\text{SG}}(P, \eta) \triangleq \frac{1}{2} \left( P + \eta - \sqrt{1 + 4P\eta} - \log \left[ \frac{\sqrt{1 + 4P\eta} - 1}{2P} \right] \right).$$

### Training

$$e_m(\eta) \leq (\sqrt{P_s} - \eta)^2 / 2$$

$$e_f(\eta) \leq \eta^2 / 2$$

# More AWGN results

— achievable performance: **joint** sync-coding  
- - - optimal detection: **separate** sync-coding

SNR = 40dB, R = 0.5C

SNR = 40dB, R = 0.8C

