

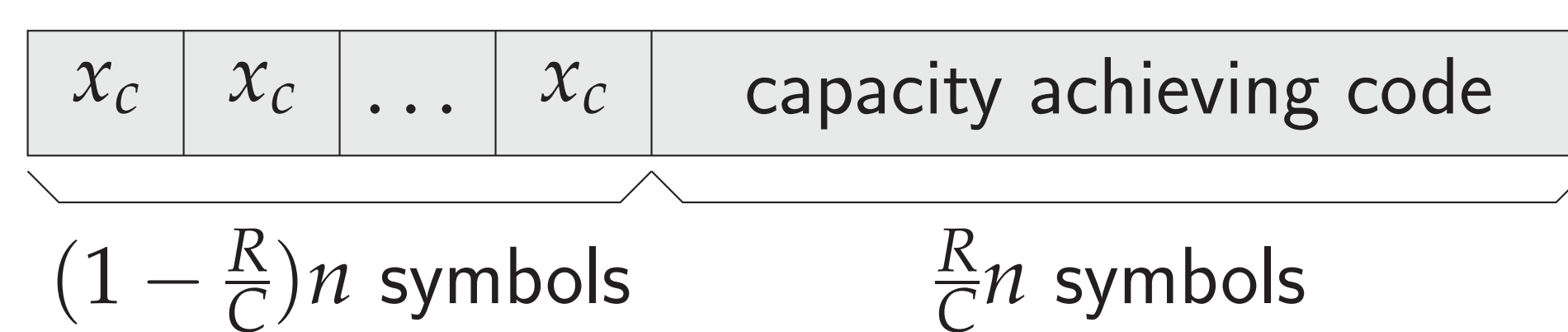
## Motivation

### Stages in Communication

- Synchronization:** detect the presence of a message and locate it.
- Coding:** encode messages to transmit reliably over noisy channels.

### Traditional Communication

- Training:** separate synchronization and coding.



- The cost of synchronization is relatively low.



### Sparse Communication

A type of communication that most transmissions have few messages.



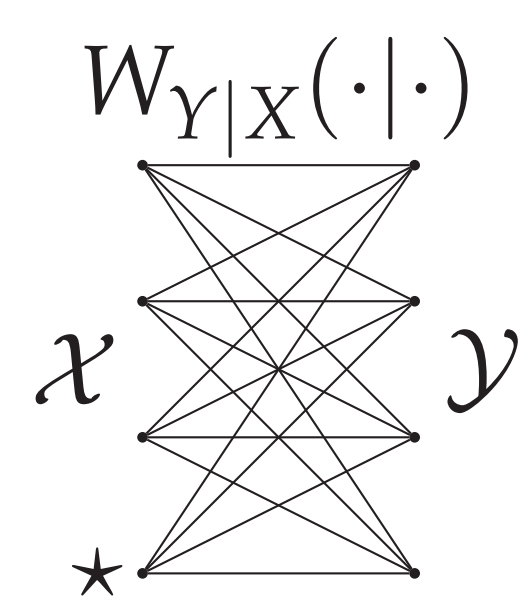
The cost of synchronization is no longer negligible!

### How to communicate efficiently?

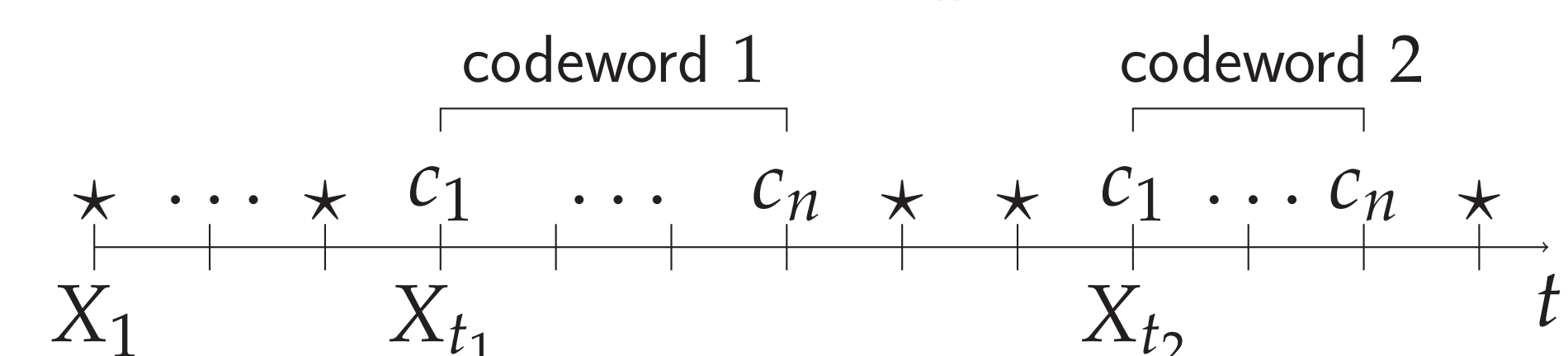
Design codes for both **synchronization** and **information transmission**.

## Problem Formulation

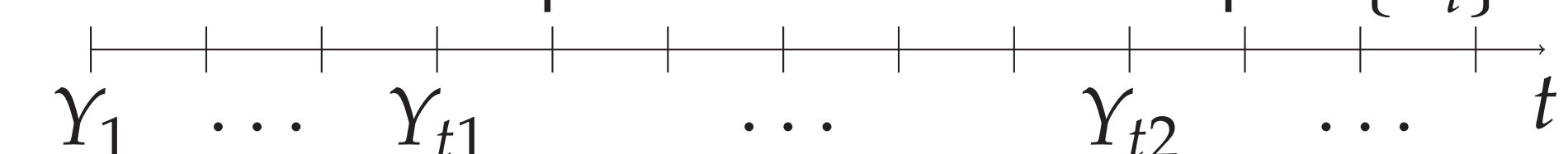
### Asynchronous channel model



- $\star$ : input symbol to model that nothing is sent.
- Tx sends codewords at time  $t_1 + 1, t_2 + 1, \dots$

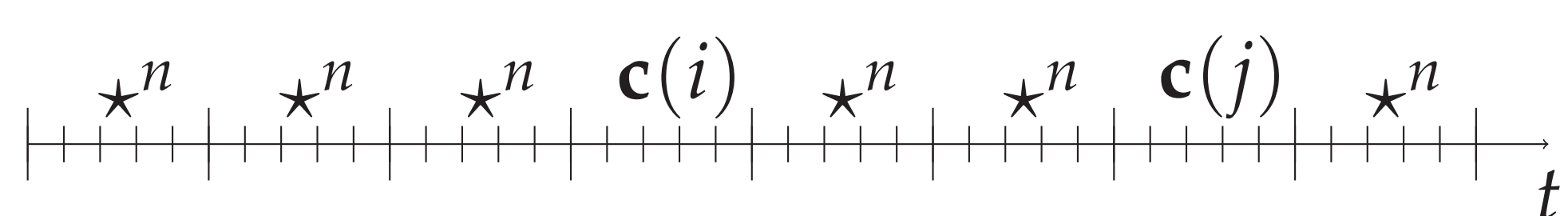


- Rx observes a sequence of channel output  $\{Y_i\}$



### Slotted simplification

Communicate in pre-defined timeslots:



synchronization  $\left\{ \begin{array}{l} \text{detect} \\ \text{locate} \end{array} \right.$   $\xrightarrow{\text{slotting}}$  detection only

### Mathematical Setup

For a channel code  $\mathcal{C} = \{X^n(k)\}$  with rate  $R$ , we have the following hypothesis testing problem:

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

Define error events

$$\mathcal{E}_{\text{Miss}} = \{H_1 \rightarrow H_0\}$$

$$\mathcal{E}_{\text{False alarm}} = \{H_0 \rightarrow H_1\}$$

and

$$P_m \triangleq \mathbb{P}[\mathcal{E}_{\text{Miss}}] \doteq \exp(-nE_m)$$

$$P_f \triangleq \mathbb{P}[\mathcal{E}_{\text{False alarm}}] \doteq \exp(-nE_f)$$

### Intuition

- We want the channel outputs corresponding to codewords be "different" from noise.
- $E_m(R)$  and  $E_f(R)$  indicate how different they can be.

### Analysis objectives

Characterize the  $E_m - E_f$  trade-off at rate  $R$ .

## Special case: $E_m = 0$

### Optimal $E_f(R)$ when $E_m = 0$

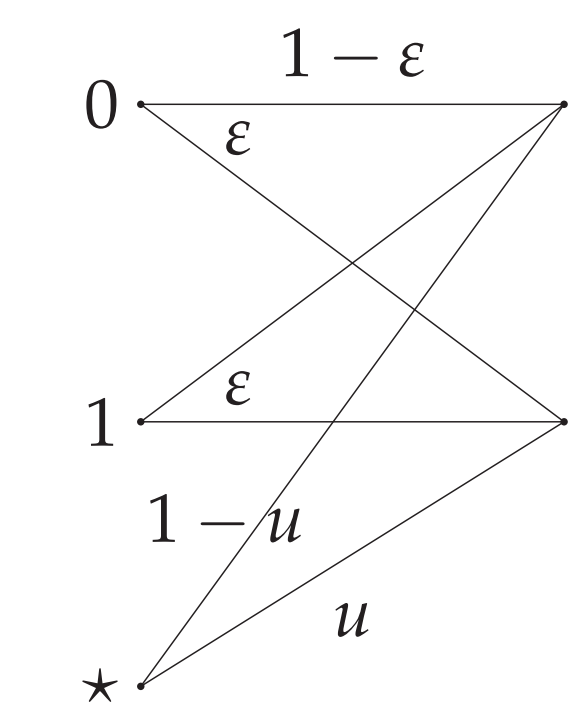
Given  $E_m = 0$  and hence  $P_m \rightarrow 0$ ,

$$E_f(R) = \max_{P_X: I(P_X, W) = R} D(P_Y \| Q_\star)$$

- i.i.d codebook with distribution  $P_X$ 
  - codeword output distribution  $P_Y$
- noise output distribution  $Q_\star = W(\cdot|\star)$ .
- use rate-achieving i.i.d codebook rather than capacity-achieving codebook.

### BSC Example

For a binary symmetric channel (BSC) with crossover probability  $\epsilon$  and  $W(\cdot|\star) = \text{Bernoulli}(u)$  ( $u \leq 0.5$ ), we can achieve



$$E_f(R) = D(\underbrace{\text{Bernoulli}(s^*)}_{\text{c.w. output dist.}} \| \underbrace{\text{Bernoulli}(u)}_{\text{noise output dist.}})$$

where  $s^* \geq 0.5$  satisfies  $H_b(s^*) - H_b(\epsilon) = R$ .

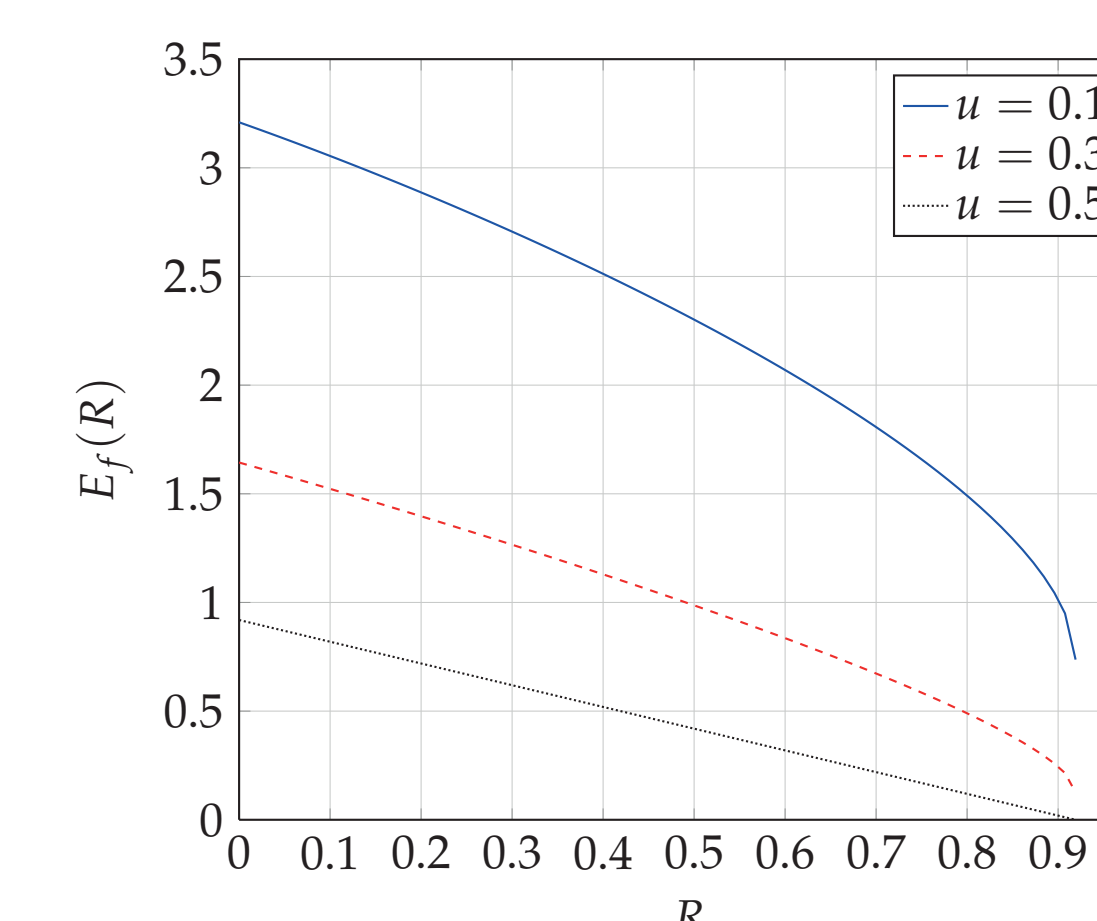


Figure:  $E_f(R)$  for BSC with  $\epsilon = 0.01$

### Comparison with training

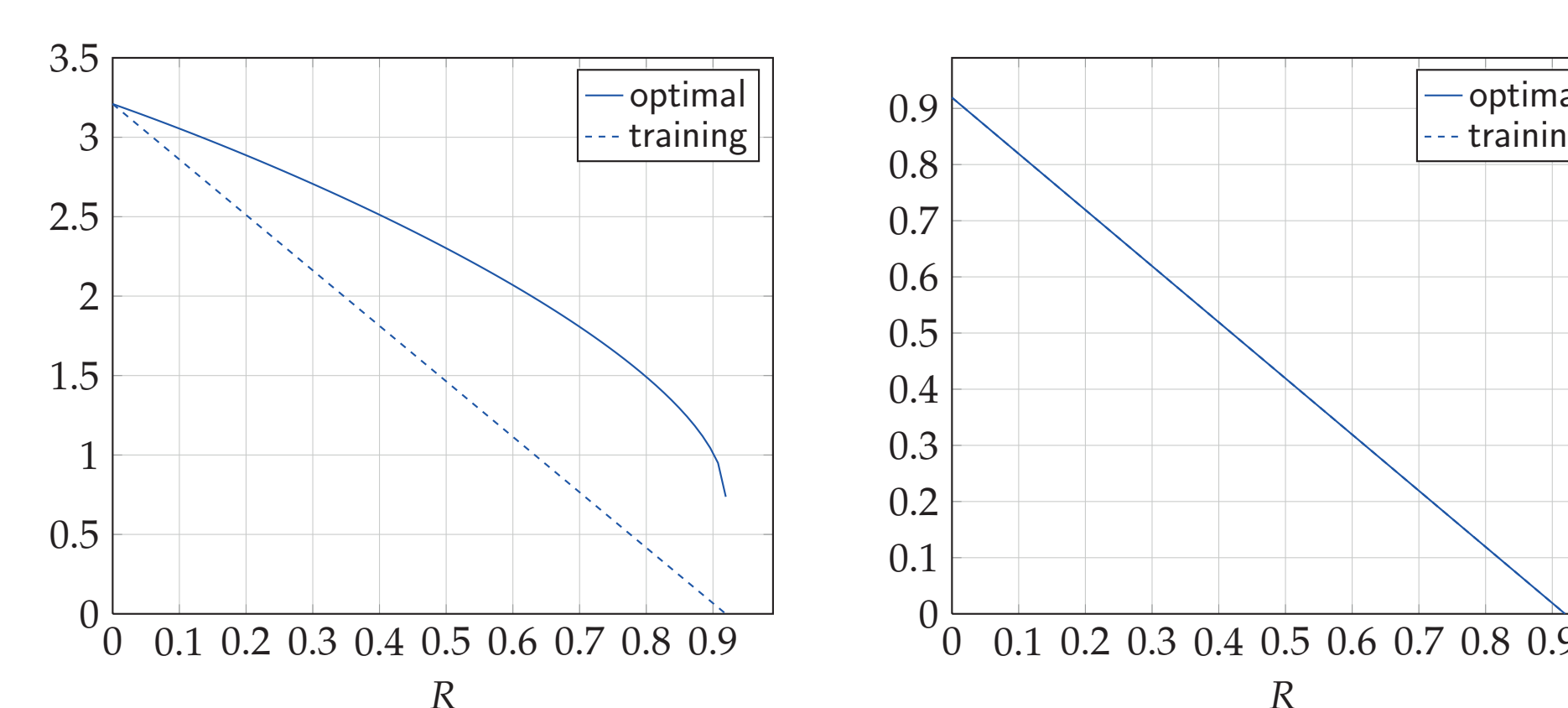


Figure: Comparison with training for BSC with  $\epsilon = 0.01$ .

Large gain over training at high rate.

## General case: $E_m \geq 0$

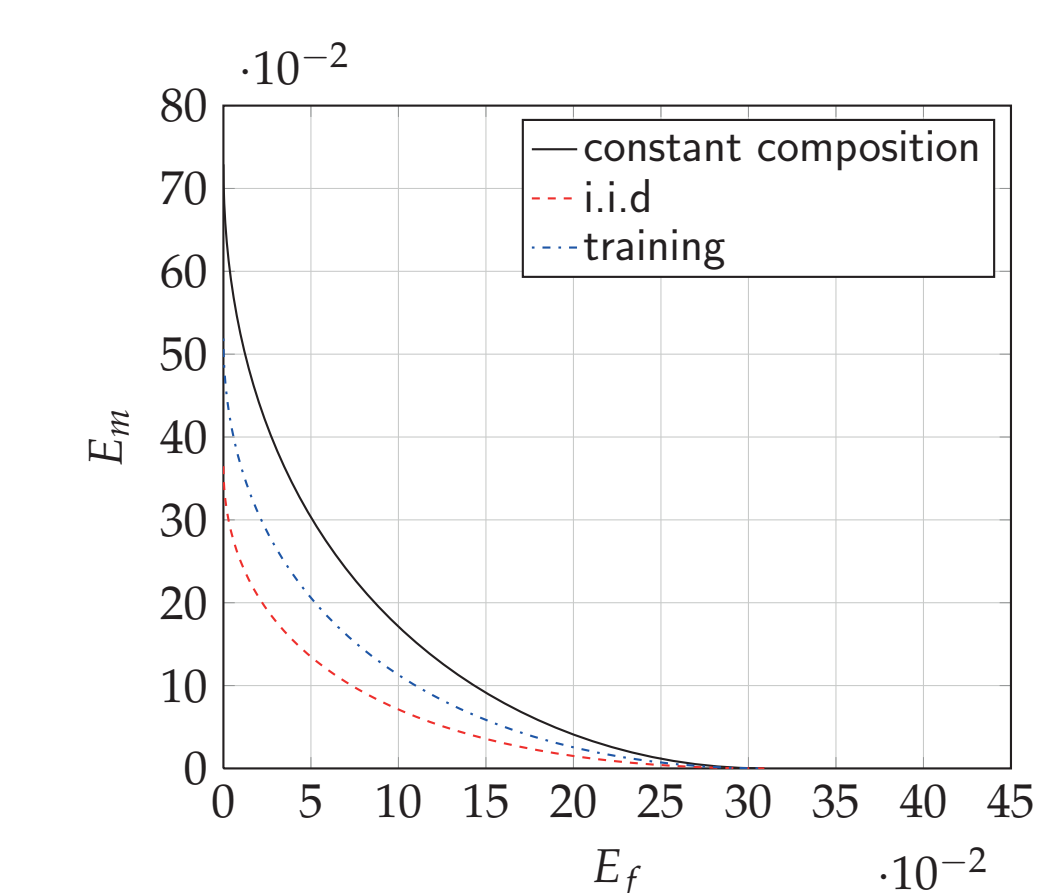
### Achievable $E_f(R)$ when $E_m \geq 0$

Given  $P_m \leq \exp(-nE_m)$ ,

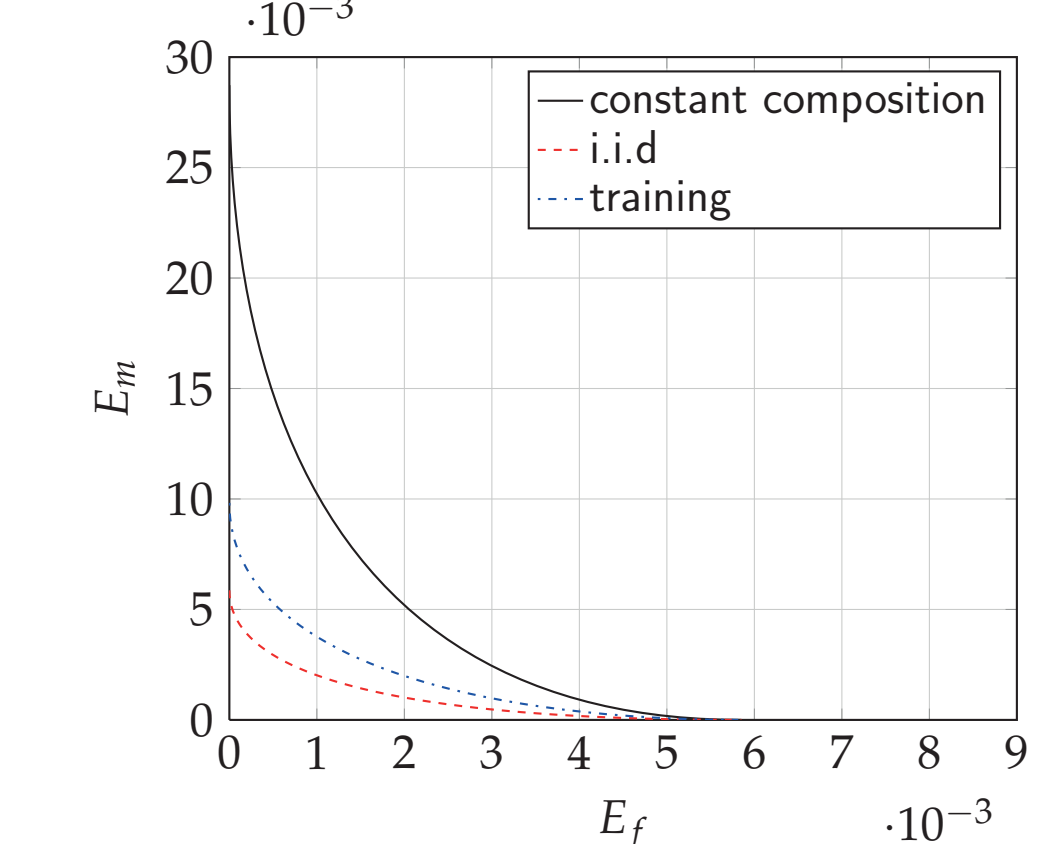
$$E_f(R, E_m) = \max_{P_X: I(P_X, W) \geq R} \min_{V: D(V \| W | P_X) \leq E_m} \left[ D(Q_V \| Q_\star) + \{I(P_X, V) - R\}^+ \right]$$

- achieved by constant composition codebook with maximizing distribution  $P_X^*$ .
- i.i.d codebook is suboptimal in general.
- non-trivial converse for DMC is difficult.

### Comparison with i.i.d codebook and training for BSC channel



(a)  $R = 0.405$



(b)  $R = 0.708$

Figure: Performance comparison between constant composition codebook, i.i.d codebook, and training for BSC with  $\epsilon = 0.05$  and  $u = 0.5$ .

Again, large gain over training at high rate.

### Conclusion

For sparse communication, designing codes for both **detection** and **information transmission** jointly achieves significantly larger detection error exponents than the traditional separate sync-coding approach.