



**TACTILENet**

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# Distributed Binary Hypothesis Testing Over Noisy Channels

Sreejith Sreekumar

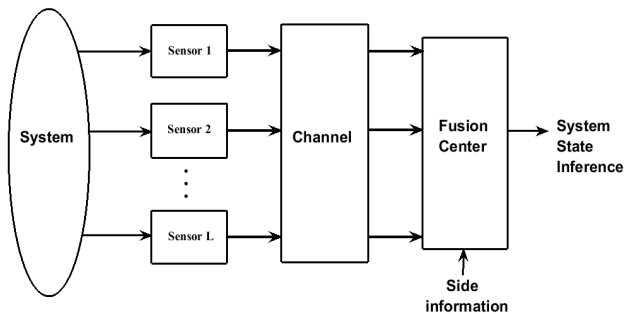
Department of Electrical and Electronic Engineering  
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Joint work with Deniz Gündüz.

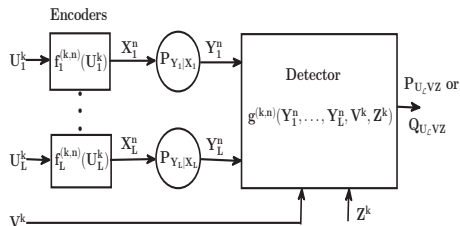
**Acknowledgement:** This work received support from the European Union's H2020 Research and Innovation Programme through project TACTILENet: Towards Agile, efficient, auTonomous and masslvely LargE Network of things (agreement 690893).



# Problem Motivation: Practical scenario



# Distributed Binary Hypothesis Testing Over Orthogonal Discrete Memoryless Channels: Model

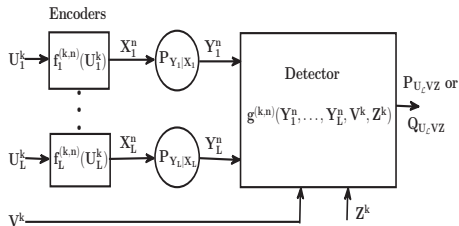


Bandwidth ratio  $\tau \triangleq \frac{n}{k}$

$H_0 : (U_{\mathcal{L}}, V, Z) \sim P_{U_{\mathcal{L}}, V, Z}$

$H_1 : (U_{\mathcal{L}}, V, Z) \sim Q_{U_{\mathcal{L}}, V, Z}$

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**Assumption:**  $P_{U_{\mathcal{L}}Z} = Q_{U_{\mathcal{L}}Z}$  and  $P_{VZ} = Q_{VZ}$ .

## Type 2 error exponent definition

For a given  $g^{(k,n)}$  (or decision region  $A \subseteq \mathcal{Y}_{\mathcal{L}}^n \times \mathcal{V}^k \times \mathcal{Z}^k$ ) and encoders  $f_1^{(k,n)}, \dots, f_L^{(k,n)}$ ,

$$\bar{\alpha} \left( k, n, f_1^{(k,n)}, \dots, f_L^{(k,n)}, g^{(k,n)} \right) \triangleq P_{Y_{\mathcal{L}}^n V^k Z^k} (A^c)$$

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$$\beta(k, \tau, \epsilon) \triangleq \inf_{\substack{f_1^{(k,n)}, \dots, f_L^{(k,n)}, g^{(k,n)} \\ n \leq \tau k}} \left\{ \begin{array}{l} \bar{\beta} \left( k, n, f_1^{(k,n)}, \dots, f_L^{(k,n)}, g^{(k,n)}, \epsilon \right) \text{ s.t.} \\ \bar{\alpha} \left( k, n, f_1^{(k,n)}, \dots, f_L^{(k,n)}, g^{(k,n)} \right) \leq \epsilon \end{array} \right\}$$

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**Question:** Does a computable characterization exist for the quantity

$$\lim_{k \rightarrow \infty} \frac{-\log(\beta(k, \tau, \epsilon))}{k} ?$$



# Testing against conditional independence problem (TACI):

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$$\Rightarrow (Y_1^n, \dots, Y_L^n, V^k, Z^k) \sim P_{Y_{\mathcal{L}}^n | Z^k} \times P_{V^k | Z^k} \times P_{Z^k}^k$$

## Previous related works:

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- 3 Optimal T2EE characterization for testing against independence problem over rate-limited channels
  - With two observers (special case with a certain Markov relation among the observed data) [Zhao-Lai (2014)]
  - With single observer having common and private bit pipes to multiple detectors [Wigger-Timo (2016)]

## Lemma

For any bandwidth ratio  $\tau > 0$ , we have

$$(i) \limsup_{k \rightarrow \infty} \frac{\log(\beta(k, \tau, \epsilon))}{k} \leq -\theta(\tau), \quad \forall \epsilon \in (0, 1).$$

$$(ii) \lim_{\epsilon \rightarrow 0} \liminf_{k \rightarrow \infty} \frac{\log(\beta(k, \tau, \epsilon))}{k} \geq -\theta(\tau).$$

where

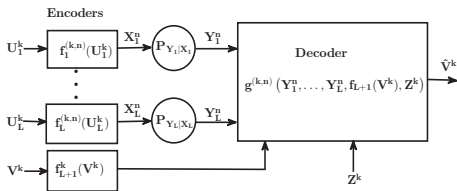
$$\theta(\tau) \triangleq \sup_k \theta(k, \tau)$$

$$\theta(k, \tau) \triangleq \sup_{\substack{f_1^{(k,n)}, \dots, f_L^{(k,n)} \\ n \leq \tau k}} \frac{D(P_{Y_{\mathcal{L}}^n V^k Z^k} \| Q_{Y_{\mathcal{L}}^n V^k Z^k})}{k}$$

# $\theta(\tau)$ for TACI

$$\begin{aligned}\theta(\tau) &= \sup_{\substack{k, f_1^{(k,n)}, \dots, f_L^{(k,n)} \\ n \leq \tau k}} \frac{D(P_{Y_{\mathcal{L}}^n V^k Z^k} \| Q_{Y_{\mathcal{L}}^n V^k Z^k})}{k} \\ &= \sup_{\substack{k, f_1^{(k,n)}, \dots, f_L^{(k,n)} \\ n \leq \tau k}} \frac{I(Y_{\mathcal{L}}^n; V^k | Z^k)}{k} \\ &= H(V|Z) - \inf_{\substack{k, f_1^{(k,n)}, \dots, f_L^{(k,n)} \\ n \leq \tau k}} \frac{H(V^k | Y_{\mathcal{L}}^n, Z^k)}{k}\end{aligned}$$

# Equivalence between TACI and L-helper JSCC problem:

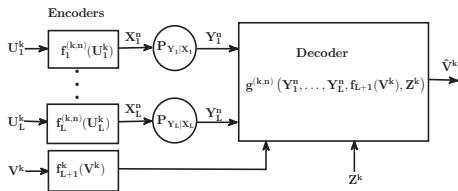


Goal: To reconstruct  $V^k$  losslessly.

What is the minimum rate  $R(\tau)$  required at encoder  $f_{L+1}^k(\cdot)$  to achieve this?



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$$R(\tau) = \inf_{k, f_1^{(k,n)}, \dots, f_L^{(k,n)}, n \leq \tau k} \frac{H(V^k | Y_{\mathcal{L}}^n, Z^k)}{k} \text{ s.t.}$$

$$(Z^k, V^k) - U_l^k - X_l^n - Y_l^n, l \in \mathcal{L}.$$

$$\theta(\tau) = H(V|Z) - R(\tau)$$

# Lower Bound for $\theta(\tau)$ :

## Theorem

$\theta(\tau) \geq H(V|Z) - R^i(\tau)$  where

$$R^i(\tau) \triangleq \inf_{W_{\mathcal{L}}} \max_{S \subseteq \mathcal{L}} F_S,$$

$$F_S = H(V|W_{S^c}, Z) + I(U_S; W_S|W_{S^c}, V, Z) - \tau \sum_{I \in S} C_I$$

$$(Z, V, U_{I^c}, W_{I^c}) - U_I - W_I, |W_I| \leq |U_I| + 4, I \in \mathcal{L} \quad (1)$$

$$I(U_{\mathcal{L}}; W_S|V, W_{S^c}, Z) \leq \tau \sum_{I \in S} C_I. \quad (2)$$

**Proof:** Source-channel separation theorem for orthogonal MAC + Berger-Tung inner bound.

# Tightness of the bounds for $L = 1$

## Lemma

For the TACI problem with  $L = 1$  and bandwidth ratio  $\tau$ ,

$$\theta(\tau) = \sup_W I(V; W|Z)$$

such that  $I(U; W|Z) \leq \tau C$ ,

$$(Z, V) - U - W, |\mathcal{W}| \leq |\mathcal{U}| + 4.$$

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$$\begin{aligned}H(V|Z, W) &\leq R', \\I(U; W|V, Z) &\leq \tau C, \\H(V|Z, W) + I(U; W|Z) &\leq \tau C + R'\end{aligned}$$

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- 3 Equivalently,

$$R(\tau) = \inf_W \max(H(V|W, Z), H(V|W, Z) + I(U; W|Z) - \tau C), \quad (3)$$

$$\text{such that } I(U; W|V, Z) \leq \tau C.$$

$$\theta(\tau) = H(V|Z) - R(\tau). \quad (4)$$

## Proof (cont):

- ④ We want to show that  $R(\tau) = H(V|W, Z)$  for some  $W$  such that  $I(U; W|Z) \leq \tau C$ .

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- 6 On the contrary, suppose that the minimum is achieved for a  $W^*$  such that  $I(U; W^*|Z) > \tau C$ .  
 $\Rightarrow R(\tau) = H(V|W^*, Z) + I(U; W^*|Z) - \tau C$  and  $I(U; W^*|V, Z) \leq \tau C$ .

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- 8 Sufficient to show that  $\exists \bar{W}$  s.t.,
  - (i)  $I(U; \bar{W}|Z) = \tau C$
  - (ii)  $H(V|\bar{W}, Z) + I(U; \bar{W}|Z) - \tau C \leq H(V|W^*, Z) + I(U; W^*|Z) - \tau C$
  - (iii)  $I(U; \bar{W}|V, Z) \leq \tau C$
  - (iv)  $(Z, V) - U - \bar{W}$

- 9 Setting  $\bar{W} = W_{p^*}$  suffices, where

$$W_p \triangleq \begin{cases} W^*, & \text{with probability } 1-p, \\ \text{constant}, & \text{with probability } p, \end{cases}$$

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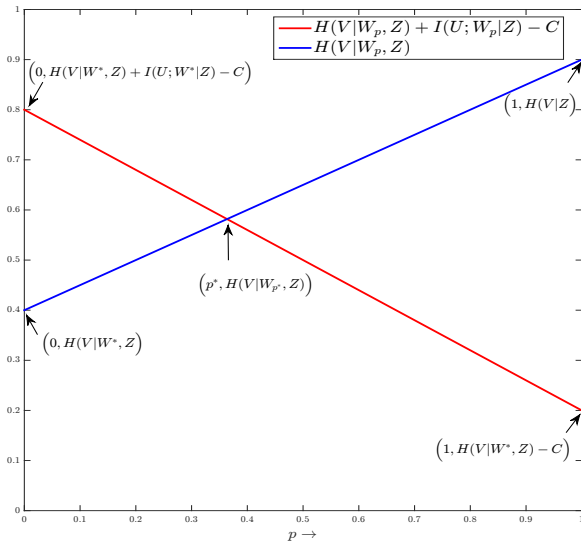
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Proof follows from the following facts.

- (i)  $I(U; W_p|Z)$  and  $I(U; W_p|V, Z)$  are decreasing functions of  $p$ .
- (ii)  $H(V|W_p, Z) + I(U; W_p|Z) - \tau C$  is a decreasing function of  $p$ .





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By the DPI for  $(V, Z) - U - W^*$ ,

$$\frac{d}{dp}H(V|W_p, Z) = I(V; W^*|Z) \leq I(U; W^*|Z) = \frac{d}{dp}H(U|W_p, Z)$$

$$\begin{aligned} \Rightarrow \frac{d}{dp} (H(V|W_p, Z) + I(U; W_p|Z) - \tau C) \\ = I(V; W^*|Z) - I(U; W^*|Z) \leq 0 \end{aligned}$$

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## Open questions:

- Is the optimal T2EE independent of  $\epsilon$ ?
- Computable characterization of the optimal T2EE for the general hypothesis testing problem.

THANKS FOR THE ATTENTION !