

Figure 1: Hypothesis Testing with One-Sided Compression Constraint.

## Distributed Hypothesis Testing

Samples  $(U^n, V^n)$  are generated according to either

$$H = 0 : (U^n, V^n) \stackrel{\text{iid}}{\sim} P_{UV} \quad \text{or} \quad H = 1 : (U^n, V^n) \stackrel{\text{iid}}{\sim} Q_{UV}$$

for  $P_{UV}$  and  $Q_{UV}$  probability distributions over a *finite* alphabet with  $P_{UV} \ll Q_{UV}$ .

**Decision center** tries to guess the underlying hypothesis  $H$ , helped by a **sensor** connected via a *noiseless zero-rate* link, so that  $k(n)$  bits are transmitted with

$$\lim_{n \rightarrow \infty} \frac{k(n)}{n} = 0.$$

### Sensor

Observes  $U^n$

Sends  $k(n)$  bits message  $M = f_n(U^n)$

### Decision Center

Observes  $V^n$  and obtains  $M$

Takes decision  $\hat{H} = g_n(M, V^n)$

## Error Criteria and Goal

A pair of encoding and test  $(f_n, g_n)$  for blocklength  $n$  achieves errors

$$\alpha_n := \mathbb{P}[\hat{H} = 1 | H = 0] \quad \text{and} \quad \beta_n := \mathbb{P}[\hat{H} = 0 | H = 1]$$

Let  $\beta_n^\varepsilon$  be the smallest achievable  $\beta_n$  when imposing a threshold  $\varepsilon \in (0, 1)$  on  $\alpha_n$

$$\beta_n^\varepsilon = \inf\{\beta_n : (f_n, g_n) \text{ such that } \alpha_n \leq \varepsilon\}.$$

*Stein's regime*: objective is to characterize the behavior of  $\beta_n^\varepsilon$  as  $n \rightarrow \infty$ .

## Han-Papamarcou-Shalaby Exponent

$\beta_n^\varepsilon$  decays exponentially with  $n$  as

$$\beta_n^\varepsilon = 2^{-n \cdot \theta^* + o(n)}, \quad \text{that is} \quad \lim_{n \rightarrow \infty} -\frac{1}{n} \log \beta_n^\varepsilon = \theta^*,$$

where  $\theta^* := \min\{D(P_{UV}^* \| Q_{UV}) : P_{UV}^* \text{ such that } P_U^* = P_U \text{ and } P_V^* = P_V\}$ .

The Han-Papamarcou-Shalaby exponent  $\theta^*$  does *not* depend on  $\varepsilon$  neither on  $k$ . It is achieved using a single bit of communication.

## Testing Against Independence

Under  $H = 1$ ,  $U^n$  and  $V^n$  are *independent* as  $Q_{UV} = P_U P_V$ , with same marginal distributions as under  $H = 0$ .

The Han-Papamarcou-Shalaby exponent is *vacuous*:  $\theta^* = 0$  (take  $P_{UV}^* = Q_{UV}$ ).  $\beta_n^\varepsilon$  cannot decrease exponentially with  $n$ , but only slower.

What is the asymptotic behavior of  $\beta_n^\varepsilon$  when testing against independence with zero-rate communication?

## Bounded Message Size

Number of transmitted bits is bounded

$$\lim_{n \rightarrow \infty} k(n) < \infty$$

### Impossibility

$\beta_n^\varepsilon$  cannot vanish when the message size is bounded

$$\lim_{n \rightarrow \infty} \beta_n^\varepsilon > 0.$$

$\Rightarrow$  Message size is the limiting parameter for independence testing.

## Unbounded Message Size

Number of transmitted bits grows sublinearly with blocklength  $n$  with

$$\lim_{n \rightarrow \infty} k(n) = \infty$$

### Naive Scheme

Sensor transmits the first  $k$  bits of  $U^n$ , for  $\tau := k/H(U)$ :

#### Sensor

Sends message  $M = U^\tau$

#### Decision Center

Performs a local test with  $(U^\tau, V^\tau)$

This achieves vanishing  $\alpha_n$  and exponential decay of  $\beta_n$  in  $k$ , so that

$$\lim_{n \rightarrow \infty} -\frac{1}{k} \log \beta_n^\varepsilon \geq \frac{I(U; V)}{H(U)}.$$

### Achievability

Using Han's scheme, we show that

$$\lim_{n \rightarrow \infty} -\frac{1}{k} \log \beta_n^\varepsilon \geq \eta(P_U, P_{V|U})$$

where  $\eta(P_U, P_{V|U}) \in [0, 1]$  is the *contraction coefficient* of channel  $P_{V|U}$  with input distribution  $P_U$ , defined as

$$\eta(P_U, P_{V|U}) := \sup_{\substack{P_{W|U} \\ W-U-V}} \frac{I(W; V)}{I(W; U)}.$$

This outperforms the naive scheme:  $\eta(P_U, P_{V|U})$  is in general not achieved by taking  $W = U$ .

### Converse

We have two partial results:

$$\text{Weak Converse: } \lim_{n \rightarrow \infty} -\frac{1}{k} \log \beta_n^\varepsilon \leq \frac{\eta(P_U, P_{V|U})}{1 - \varepsilon},$$

which gives a proper converse in the limit  $\varepsilon \rightarrow 0$ ,

$$\text{Strong Converse: } \lim_{n \rightarrow \infty} -\frac{1}{k} \log \beta_n^\varepsilon \leq \eta(P_U, P_{V|U}) \text{ when } \lim_{n \rightarrow \infty} \frac{k(n)}{\sqrt{n}} = \infty, \quad (1)$$

yielding a converse for all  $\varepsilon$  provided  $k(n)$  grows sufficiently fast as in (1).

$\Rightarrow \beta_n^\varepsilon$  decays exponentially with  $k(n)$ . Under (1) we get

$$\beta_n^\varepsilon = 2^{-k \cdot \eta(P_U, P_{V|U}) + o(k)},$$

whereas in general a  $(1 - \varepsilon)^{-1}$  gap between exponents remains.

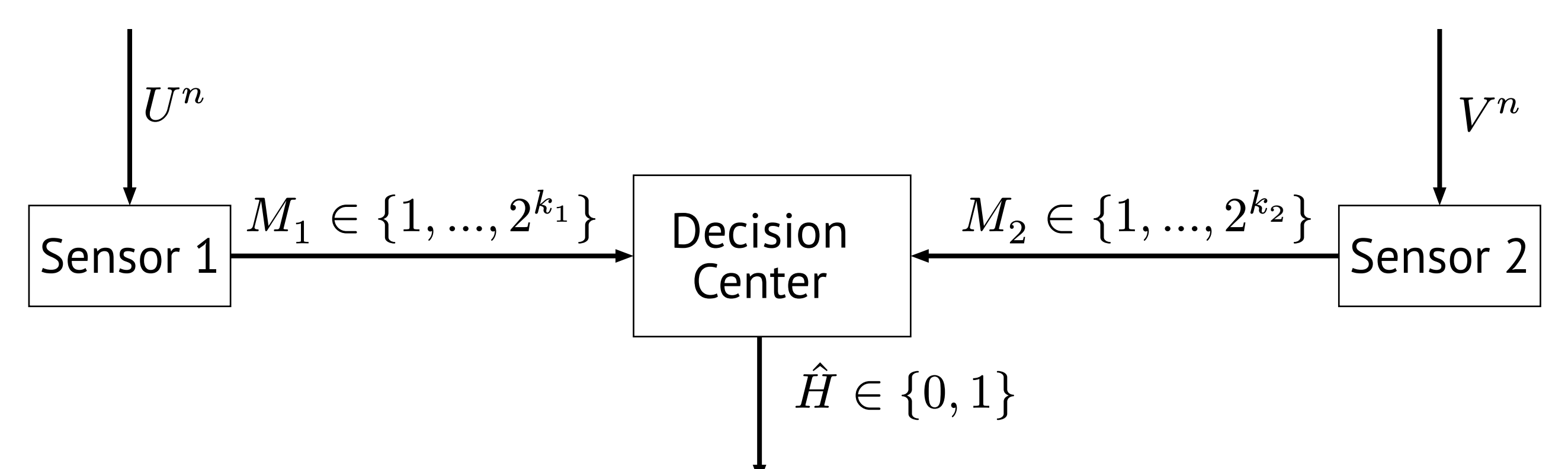


Figure 2: Hypothesis Testing with Two-Sided Compression Constraint.

## Two-Sided Compression

Both  $U^n$  and  $V^n$  are observed remotely via *noiseless zero-rate* links.

The Han-Papamarcou-Shalaby exponent still holds.

$\Rightarrow$  Asymptotic of  $\beta_n^\varepsilon$  is governed by  $\min(k_1, k_2)$ :

- For *bounded*  $\min(k_1, k_2)$ , vanishing error is still impossible

$$\lim_{n \rightarrow \infty} \beta_n^\varepsilon > 0.$$

- For *unbounded*  $\min(k_1, k_2)$ ,  $\beta_n^\varepsilon$  decays exponentially with  $\min(k_1, k_2)$ .