

# Discussion on “Multiscale Change Point Inference”

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We congratulate the authors on a very interesting paper. The paper sheds lights on a problem of great interest, and the theory and methods developed are potentially useful in many applications.

In [5], we have investigated the problem from the variable selection perspective. Consider a linear model

$$Y = X\beta + z, \quad X = X_{n,n}, \quad z \sim N(0, I_n), \quad (1)$$

where  $X(i, j) = 1\{j \geq i\}$ ,  $1 \leq i, j \leq n$ , and  $\beta$  is a sparse vector, containing a small fraction of nonzeros (i.e., “jumps”). In effect,  $X\beta$  is a block-wise constant vector, so (1) is a change-point model. We are interested in identifying all jumps.

Fixing  $\vartheta \in (0, 1)$  and  $r > 0$  and letting  $\epsilon_n = n^{-\vartheta}$ ,  $\tau_n = \sqrt{2r \log(n)}$ , we consider a “Rare and Weak” setting where

$$\beta_j \stackrel{iid}{\sim} (1 - \epsilon_n)\nu_0 + \epsilon_n\nu_{\tau_n}, \quad (\nu_a: \text{point mass at } a). \quad (2)$$

See [5] for more general case and see [1, 3, 5] for the subtlety of model (2). The *minimax Hamming selection error* is then

$$\text{Hamm}_n^*(\vartheta, r) = \inf_{\hat{\beta}} \left[ \sum_{j=1}^n P \left\{ \text{sgn}(\hat{\beta}_j) \neq \text{sgn}(\beta_j) \right\} \right].$$

We showed in [5] that

$$\text{Hamm}_n^*(\vartheta, r) = \begin{cases} L_n \cdot n^{(1-\vartheta-r/4)} + o(1), & r/\vartheta \leq 6 + 2\sqrt{10}, \\ L_n \cdot n^{(1-3\vartheta-(r/2-\vartheta)^2/(2r))} + o(1), & r/\vartheta > 6 + 2\sqrt{10}, \end{cases}$$

where  $L_n$  is a generic *multi-log*( $n$ ) term. This implies a *watershed* phenomenon (also found in [1, 3, 2, 4], but in different settings), which can be captured by so-called *Phase Diagram*; see Figure 1.

Moreover, we developed in [5] a procedure called *CASE* which achieves the minimax rate above. *CASE* is a two-stage Screen and Clean method, where at the heart is *multivariate  $\chi^2$ -screening* guided by a sparse graph, constructed based on the matrix  $X$ .

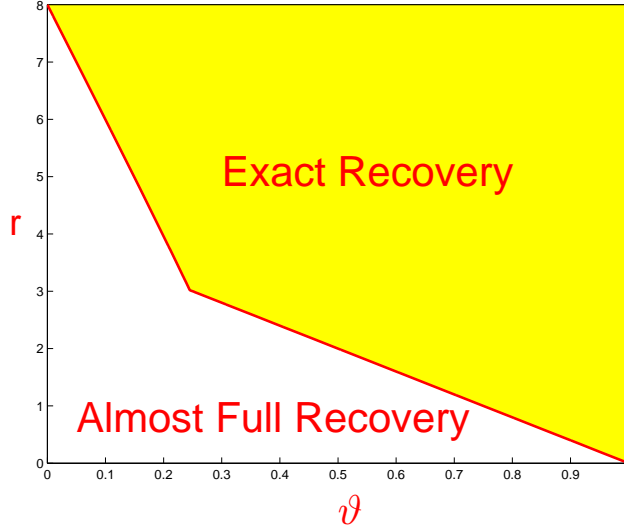


Figure 1: Phase Diagram for change-point model. In the two-dimensional phase space  $\{(\vartheta, r) : 0 < \vartheta < 1, r > 0\}$ , the curve  $r = \rho_0(\vartheta)$  separates the phase space into two sub-regions, where  $\rho_0(\vartheta) = \max\{4(1 - \vartheta), (4 - 10\vartheta) + 2\sqrt{[(2 - 5\vartheta)^2 - \vartheta^2]_+}\}$ . For  $(\vartheta, r)$  in the interior of the region above the curve, it is possible to identify all jumps (say, by using CASE) with high probability. For  $(\vartheta, r)$  in the interior of the region below the curve,  $1 \ll \text{Hamm}_n(\vartheta, r)^* \ll n\epsilon_n$ , and it is impossible to identify all jumps, but it is possible to identify most of them (say, by using CASE).

## References

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