

1 Introduction

We investigate the impact of the network configuration on the level of **favorable propagation** for a cell-free (CF) Massive MIMO network. Leveraging users' spatial diversity, we formulate a user grouping and scheduling optimization problem. The formulated optimization problem is NP-hard. We design an efficient randomization algorithm based on **semidefinite relaxation** method to efficiently find a sub-optimal solution.

2 System Model

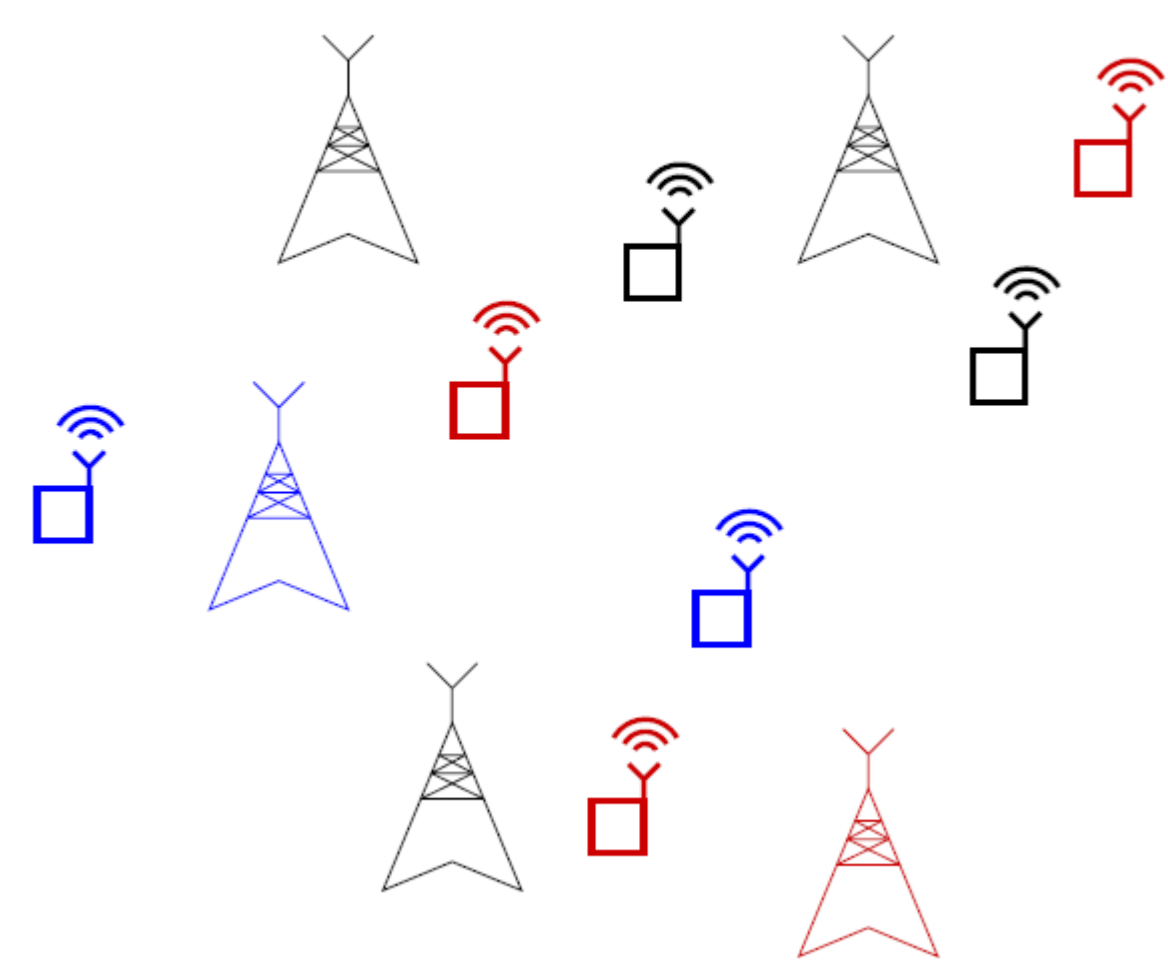


Figure 2: Cell-free Massive MIMO

- M single antenna APs serve simultaneously K single omni-directional antenna users ($K \ll M$)
- The m -th AP performs **minimum mean-square error (MMSE)** channel estimation

$$\hat{g}_{mk} = \frac{\sqrt{\rho_p} \beta_{mk}}{\rho_p \beta_{mk} + 1} (\sqrt{\rho_p} g_{mk} + \mathbf{n}_{m,p} \mathbf{q}_k^\dagger), k = 1, \dots, \tau$$

where,

- g_{mk} : **channel coefficient** between the k -th user and the m -th AP.
- \mathbf{q}_k : training sequence of the k th user.
- β_{mk} : **large scale fading** coefficients.
- ρ_p : **transmit power** during training phase.
- $\mathbf{n}_{m,p}$: AWGN vector at the m -th AP.
- τ : **uplink training duration** with $\tau < T_c$ (**coherence interval**).

3 Which users can be active simultaneously?

Favorable propagation: **mutual orthogonality** between users' vector wireless channel

$$\mathbf{g}_k^\dagger \mathbf{g}_j = \begin{cases} 0 & \text{if } k \neq j, \\ \|\mathbf{g}_k\|^2 \neq 0 & \text{otherwise,} \end{cases}$$

Asymptotically,

$$\frac{\mathbf{g}_k^\dagger \mathbf{g}_j}{M} \rightarrow 0, M \rightarrow \infty \text{ for } k \neq j,$$

which is equivalent to

$$\frac{\sum_{m=1}^M \sqrt{\beta_{m,k}} \sqrt{\beta_{m,j}} h_{m,k}^* h_{m,j}}{M} \rightarrow 0 \text{ for } k \neq j,$$

where

- $h_{mk} \sim \mathcal{CN}(0, 1)$: **small-scale fading** coefficients.

Alternative: consider the **complementary CDF** of the inner product of two given users' channel

$$P_\theta = \Pr \left\{ \frac{\mathbf{g}_k^\dagger \mathbf{g}_j}{M} \geq \theta \right\}$$

Objective: making $P_\theta, \forall \theta \geq 0$ very small to achieve **NEAR ORTHOGONALITY** between users' channel vectors, and therefore **FAVORABLE PROPAGATION**.

Invoking **Chebyshev's inequality**, P_θ can be lower-bounded by

$$P_\theta = \Pr \left\{ \frac{\mathbf{g}_k^\dagger \mathbf{g}_j}{M} \geq \theta \right\} \leq \frac{1}{1 + \frac{\theta^2}{\sum_{m=1}^M \beta_{m,k} \beta_{m,j}}}$$

Challenge: design a scheme to minimize P_θ .

4 Graphical Modeling and proposed solution

4.1 Scheduling design

- Step 1**: Construct a **spatial correlation** graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ that captures the level of **favorable propagation** for a set of users which are active simultaneously.

- \mathcal{V} : set of vertices stands for the users in the coverage area.

- Each edge $e_{k,j} \in \mathcal{E}$ is associated with a weight $w_{k,j} \triangleq \sum_{m=1}^M \beta_{mk} \beta_{mj}$, directly related to the spatial correlation between two users' channel.

- Step 2**: **Group active users** such that the spatial correlation between their channels is **minimized**.

4.2 Problem formulation and algorithm design

Define the following variable

$$x_{k,c} = \begin{cases} 1 & \text{if user } k \text{ is allocated to the } c\text{-th group} \\ 0 & \text{otherwise} \end{cases}$$

The user grouping problem is formulated as

$$\begin{aligned} \max_{x_{k,c} \in \{0,1\}, \forall c, \forall k} & \sum_{c=1}^C \sum_{k \in \mathcal{V}} \sum_{j \in \mathcal{V}, j \neq k} w_{k,j} (1 - x_{k,c}) x_{j,c} \\ \text{s.t.} & \sum_{c=1}^C x_{k,c} \leq \alpha, \forall k \in \mathcal{V}, \\ & \sum_{k \in \mathcal{V}} x_{k,c} \leq \tau, \forall c = 1, \dots, C, \end{aligned} \quad (1)$$

where,

- C : total number of groups.
- α : maximum number of groups to which a user can belong at the same time.

Lemma 1: Computational tractability

Problem (1) is **NP-hard** in general.

GOAL: Design a **low-complexity** algorithm to **sub-optimally** solve problem (1).

Define following variables and changes of variables

$$\begin{aligned} \mathbf{x}_c & \triangleq (x_{1,c}, \dots, x_{K,c})^\top, \mathbf{y}_c \triangleq 2\mathbf{x}_c - \mathbf{1}_K \\ \mathbf{W} & \triangleq \begin{pmatrix} 0 & w_{2,1} & \dots & w_{K,1} \\ w_{1,2} & 0 & \dots & w_{K,2} \\ \vdots & \vdots & \ddots & \vdots \\ w_{1,K} & w_{2,K} & \dots & 0 \end{pmatrix} \end{aligned}$$

where,

- $\mathbf{1}_K$: entry one column vector.

Combining **SEMIDEFINITE RELAXATION** method with the **SCHUR COMPLEMENT**, problem (1) can be relaxed as

$$\begin{aligned} \max_{Y_c \succeq 0, \forall c} & \frac{1}{4} \sum_{c=1}^C (\varsigma - \text{tr}(\mathbf{W} Y_c)) \\ \text{s.t.} & \sum_{c=1}^C \mathbf{y}_c \leq \bar{\alpha} \\ & \text{tr}(\text{diag}(\mathbf{y}_c)) \leq \bar{\tau}, \forall c \\ & \text{diag}(Y_c) = \mathbf{1}_K \\ & \begin{pmatrix} Y_c & \mathbf{y}_c \\ \mathbf{y}_c^\top & 1 \end{pmatrix} \succeq 0, \forall c \end{aligned} \quad (2)$$

Problem (2) is a **standard convex optimization problem** and can be efficiently solved using CVX.

We develop a randomized procedure, in the vein of **Gaussian randomization**, to convert the optimal solution of (2) into a feasible solution to problem (1).

Algorithm 1 A randomized algorithm to solve problem (1)

- input** an optimal solution Y_c^* , $\forall c$ to problem (2).
- Generate $\xi_c \sim \mathcal{N}(\mathbf{0}, Y_c^*)$, $\forall c$;
- Set $\bar{\xi}_c = \xi_c / \text{tr}(\text{diag}(\xi_c))$, $\forall c$;
- Generate L vector samples $\bar{\mathbf{y}}_c^l$, $l = 1, \dots, L$ feasible for problem (1) such that each entry $\bar{y}_{k,c}^l$, $k = 1, \dots, C$ is drawn from the following distribution:

$$\bar{y}_{k,c}^l = \begin{cases} 1 & \text{with probability } (1 + \bar{\xi}_{k,c})/2 \\ -1 & \text{with probability } (1 - \bar{\xi}_{k,c})/2 \end{cases}$$

- Compute $l^* = \arg \max_{l=1, \dots, L} \sum_{c=1}^C (\varsigma - (\bar{\mathbf{y}}_c^l)^\top \mathbf{W} \bar{\mathbf{y}}_c^l)$;
- output** the solution $\bar{\mathbf{y}}_c = \bar{\mathbf{y}}_c^{l^*}$, $\forall c$.

4.3 Bandwidth allocation problem

The **bandwidth allocation problem** is formulated as

$$\begin{aligned} \max_{0 \leq \gamma_c \leq 1, \forall c} & \sum_{c, k \in \Gamma(c)} \gamma_c \bar{R}_{k,c} \\ \text{s.t.} & \bar{R}_k \leq \sum_{c=1}^C \gamma_c \bar{R}_{k,c}, \forall k \\ & \sum_{c=1}^C \gamma_c \leq 1 \end{aligned} \quad (3)$$

The **rate** of the k th user in group c is given by

$$\bar{R}_{k,c} = \mathcal{B} \frac{T_c - |\Gamma(c)|}{T_c} \log_2 \left(1 + \frac{\rho_d \left(\sum_{m=1}^M \nu_{mk} \right)^2}{\rho_d \sum_{m=1}^M \sum_{k' \in \Gamma(c), k' \neq k} \nu_{mk'} \beta_{mk} + 1} \right)$$

where,

- \mathcal{B} : **bandwidth** of the system.
- $\nu_{mk} \triangleq \frac{\rho_p \beta_{mk}^2}{1 + \rho_p \beta_{mk}}$: **variance** of \hat{g}_{mk} .
- ρ_d : **downlink transmit power**.
- $\Gamma(c)$: set of users that belong to group c .

Problem (3): a **convex linear** optimization problem. Optimal solution: **interior-point method**.

5 Numerical Results

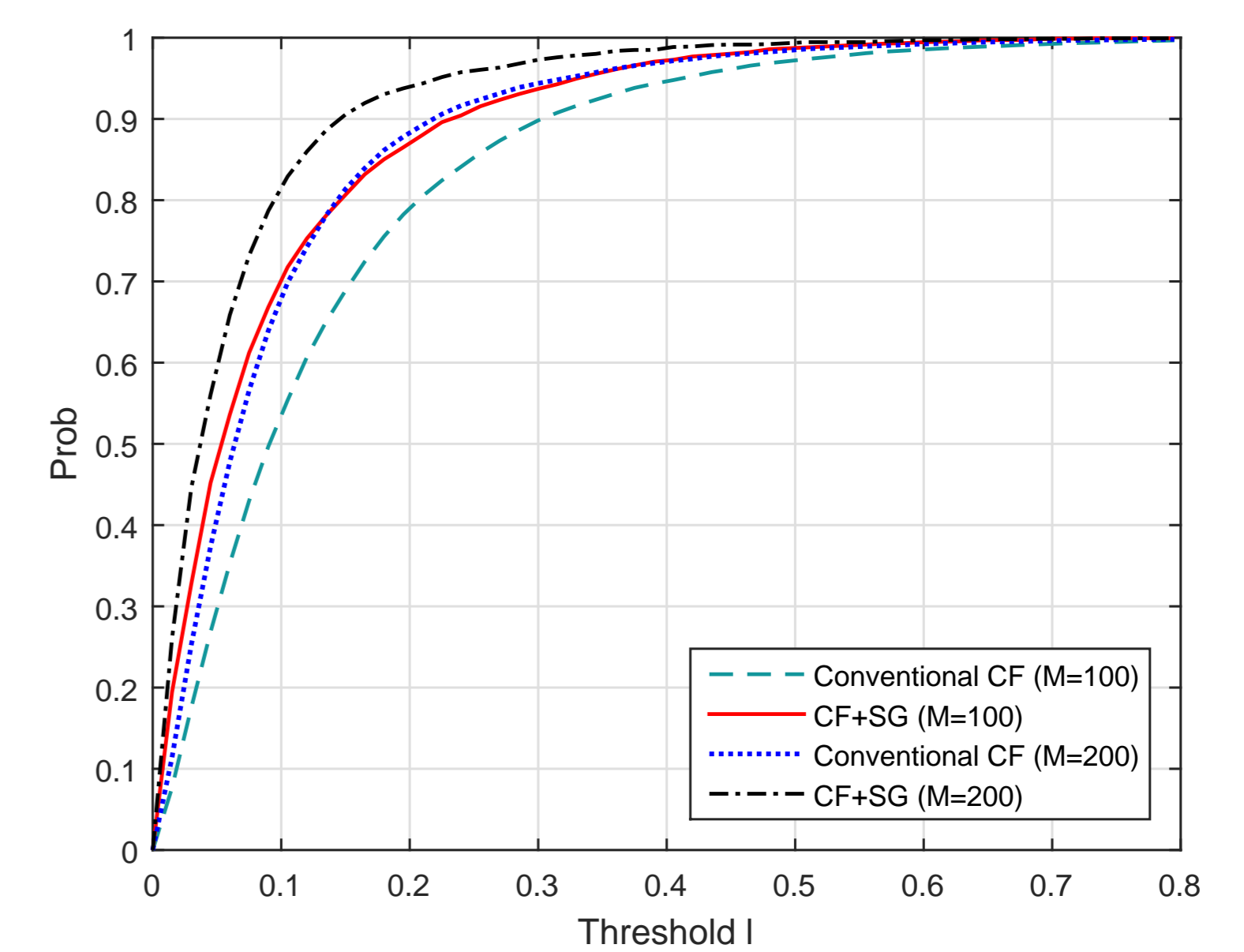


Figure 3: Comparison of CDFs of normalized large-scale fading correlation for $K = 20, \alpha = 6, C = 4$

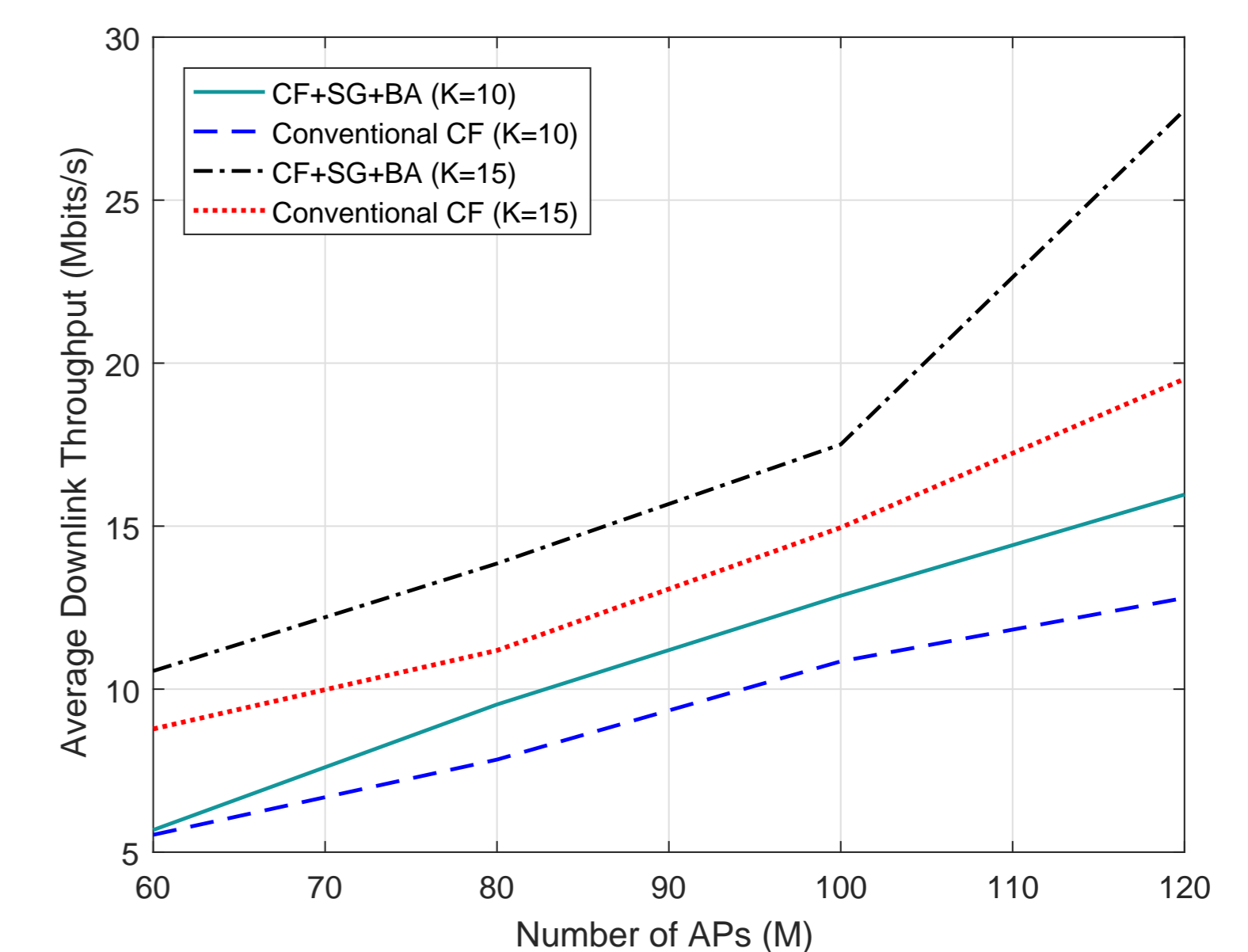


Figure 4: Average Downlink Throughput versus the number of APs and different K values ($\tau = K$)

6 Acknowledgements

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