Multivector Reduced-set Matching Pursuit (MRMP): A Low-Complexity Approach for Joint Sparse Recovery with Virtual Data Synthesis

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***Abstract*—This paper explores joint sparse recovery in the context of cooperative compressed spectrum sensing. We introduce the Multi-Vector Reduced-Set Matching Pursuit (MRMP) algorithm, an enhanced version of the Reduced-Set Matching Pursuit (RMP) method, designed to efficiently process multivector models without redundant computations. Unlike conventional approaches that handle each vector separately, MRMP jointly exploits the underlying sparsity structure, leading to improved performance. We benchmark MRMP against Simultaneous Orthogonal Matching Pursuit (SOMP) and further enhance recovery accuracy by incorporating a virtual data synthesis technique that boosts the signal-to-noise ratio (SNR) before reconstruction. Simulation and real-world SDR implementation results demonstrate that MRMP significantly reduces computational complexity while maintaining high recovery accuracy. Overall, the proposed method improves processing speed by approximately 2.5 times compared to SOMP and by a factor of 23 compared to cooperative RMP recovery using raw compressed measurements.**

***Index Terms*—Joint Sparse Recovery, Compressed Spectrum Sensing, Multi-Vector Processing, Matching Pursuit, Reconstruction, Computational Efficiency.**

I. INTRODUCTION

Compressed sensing (CS) is a signal processing technique for reconstructing a signal from a limited number of samples, which is far below the Nyquist rate, provided that the signal is sparse in some domain [1]. CS has found applications in various fields, including imaging, radar, and remote sensing [2]. In traditional CS, the dictionary matrix is assumed to be known precisely. However, in real-world scenarios, this matrix can be affected by noise and fluctuations [2].

The sparse recovery problem, also known as the sparse linear inverse problem, is widely applied across various fields, including data science, signal processing, and communications engineering. It plays a fundamental role in CS and contributes to feature selection and the design of efficient convolutional neural networks in deep learning [3]. Cooperative sensing extends the principles of CS to scenarios in which multiple sensors collaborate to recover a signal [4]. Joint sparse recovery (JSR) is a key technique in cooperative sensing, aiming to simultaneously recover jointly sparse signals from multiple measurement vectors [5], [6]. Joint-sparse techniques can be applied to Direction-Of-Arrival (DOA) estimation [5], [6].

Existing JSR algorithms, such as Simultaneous Orthogonal Matching Pursuit (SOMP) and Orthogonal Least Squares (OLS), have shown promise in recovering jointly sparse signals [7]. Despite the progress in JSR, challenges remain in developing efficient and robust algorithms that can handle dictionary mismatches and noisy measurements. Current research focuses on improving the accuracy and speed of JSR algorithms, as well as developing methods that are less sensitive to noise and model errors [2]. An approach involves algorithms to solve the joint sparse recovery problem using regularization-based methods [8].

An earlier study [9] demonstrated that Fast Matching Pursuit (FMP) offers notable computational speed advantages; however, it significantly lags behind OMP in terms of reconstruction accuracy. In this paper, we introduce a multi-vector version of the Reduced-set Matching Pursuit (RMP) algorithm [10] (MRMP), for JSR models. Our work modifies the RMP algorithm to handle multiple measurement vectors, making it suitable for JSR problems. While a direct comparison with OMP is not favorable, we introduce a virtual data synthesis (VDS) technique to enhance the signal-to-noise ratio (SNR) for both MRMP and SOMP.

The remainder of this paper is structured as follows. In Section II, we provide an overview of CS in cooperative networks, discussing its advantages and challenges in multi-user environments. Section III introduces the proposed MRMP algorithm, detailing its formulation, key modifications to the traditional RMP approach, and the integration of VDS to enhance performance. Also it presents a complexity analysis of

MRMP in comparison to existing joint sparse recovery algorithms such as SOMP and RMP, highlighting computational trade-offs. In Section IV, we conduct extensive simulations to evaluate the performance of MRMP in terms of detection probability, false alarm rate, and recovery accuracy under various noise conditions and network sizes. Section V contains the SDR validation of the found results to further accredit the proposed approach efficacy. Finally, Section VI concludes the paper with a summary of key findings and potential future research directions.

II. Compressed Sensing in Cooperative Networks

CS has revolutionized signal acquisition and recovery, especially in resource-limited environments where efficiency is crucial. This technique is particularly valuable in cooperative networks, where multiple sensors jointly monitor sparse signals while optimizing resource usage. In such setups, L users or sensors collectively observe a sparse signal, enabling a significant reduction in sampling rates below the Nyquist limit without compromising recovery accuracy [5]. Recent advancements have demonstrated CS's effectiveness in wireless sensor networks and Internet of Things (IoT) applications [9]. For example, [11] introduced a distributed CS framework for cooperative spectrum sensing, achieving reliable signal recovery with minimal communication overhead. Additionally, [9] compares the performance of the recovery algorithms from both categories: convex optimization and greedy family. Convex optimization in more accurate and estimates the spectrum with noise floor (useful for SNR estimation)

Authors in [12], [13] examine the impact of fusion rules on support tracking and compare cooperative detection probability and false alarm rate (Q_d, Q_f) with other existing methods. While the proposed approaches demonstrate superior performance, they are computationally demanding, making them less suitable for real-time applications where speed is a critical factor. JSR leverages inter-sensor correlations to enhance detection in noisy, bandwidth-limited environments. However, conventional CS methods like OMP face scalability issues due to high computational demands, highlighting the need for optimized algorithms for multi-user cooperative systems.

III. Multi-Vector Reduced-Set Matching Pursuit (MRMP): Algorithm and Analysis

In cooperative cs networks, L users observe a sparse signal through a sensing matrix, aiming to recover it jointly with reduced sampling and computational burden. The proposed algorithm extends the RMP framework [10] to efficiently handle multiple measurement vectors, leveraging VDS and adaptive support selection. Consider a system model where L cooperative sensors acquire sparse spectrA $\mathbf{X} \in \mathbb{C}^{N\times L}$ through a measurement matrix $\mathbf{A} \in \mathbb{C}^{M\times N}$ $(M \ll N)$:

$$\mathbf{y} = \mathbf{A}\mathbf{X} + \mathbf{w}, \tag{1}$$

Algorithm 1 Multi-Vector Reduced-Set Matching Pursuit (MRMP)

Require: Sensing matrix $\mathbf{A}$, measurement matrix $\mathbf{Y}$, sparsity level K, tolerance tol, parameters b, and a

Ensure: Reconstructed spectrum matrix $\hat{\mathbf{X}}$

$\tilde{\mathbf{Y}} \leftarrow \mathbf{Y} \cdot (\sim \text{eye}(L))/(L-1)$ ▷ VDS technique [13]

$\mathbf{r}^{[0]} \leftarrow \tilde{\mathbf{Y}}, \hat{\mathbf{X}}^{[0]} \leftarrow \mathbf{0}_{N,L}, \mathbf{T}^{[0]} \leftarrow \emptyset$ ▷ Initializations

for iter $= 1$ to K **or** $\|\mathbf{r}^{[\text{iter}]}\|_{\text{fro}} < tol$ **do**

  $\mathbf{cr}^{[\text{iter}]} \leftarrow |\mathbf{A}^T\mathbf{r}^{[\text{iter}-1]}|$ ▷ Compute correlation

  $\mathbf{cr}^{[\text{iter}]} \leftarrow \mathbf{cr}^{[\text{iter}]} / \max(\mathbf{cr}^{[\text{iter}]}, [], 1)$ ▷ Normalize

  $[\sim, \mathbf{J}^{[\text{iter}]}] \leftarrow \mathbf{maxk}(\mathbf{cr}^{[\text{iter}]}(:), \text{round}(b \cdot K))$ ▷ Select the most correlated atoms

  $[\mathbf{ind}, \sim] \leftarrow \text{ind2sub}(\text{size}(\mathbf{cr}^{[\text{iter}]}), \mathbf{J}^{[\text{iter}]})$

  $\mathbf{W}^{[\text{iter}]} \leftarrow \{\mathbf{ind} \mid \mathbf{cr}^{[\text{iter}]}(\mathbf{ind}) > a\}$ ▷ Thresholding

  $\mathbf{T}^{[\text{iter}]} \leftarrow \text{unique}([\mathbf{T}^{[\text{iter}-1]}; \mathbf{W}^{[\text{iter}]}])$ ▷ Update support

  $\hat{\mathbf{X}}^{[\text{iter}]}(\mathbf{T}^{[\text{iter}]}, :) \leftarrow \mathbf{A}(:, \mathbf{T}^{[\text{iter}]})^{\dagger}\tilde{\mathbf{Y}}$ ▷ Solution update

  $[\sim, \mathbf{idx}] \leftarrow \mathbf{maxk}(|\hat{\mathbf{X}}^{[\text{iter}]}|, K, 1)$

  $\hat{\mathbf{X}}^{[\text{iter}]} \leftarrow \mathbf{H}_K(\hat{\mathbf{X}}^{[\text{iter}]}, \mathbf{idx})$ ▷ Enforce sparsity

  $\mathbf{r}^{[\text{iter}]} \leftarrow \tilde{\mathbf{Y}} - \mathbf{A}\hat{\mathbf{X}}^{[\text{iter}]}$ ▷ Update residual

  $\mathbf{T}^{[\text{iter}]} \leftarrow \text{find}(\text{sum}(\hat{\mathbf{X}}^{[\text{iter}]} \neq 0, 2))$ ▷ Update active support

  if $\|\mathbf{r}^{[\text{iter}]}\|_{\text{fro}} < tol$ **or** $\text{size}(\mathbf{T}^{[\text{iter}]}, 1) > K$ **then**

    break

  end if

end for

return $\hat{\mathbf{X}}$

where $\mathbf{w}$ represents measurement noise. To enhance the SNR by a factor of $L-1$, MRMP synthesizes virtual measurements as proposed in [12]:

$$\tilde{\mathbf{y}} = \mathbf{y} \cdot (\sim \text{eye}(L))/(L-1), \tag{2}$$

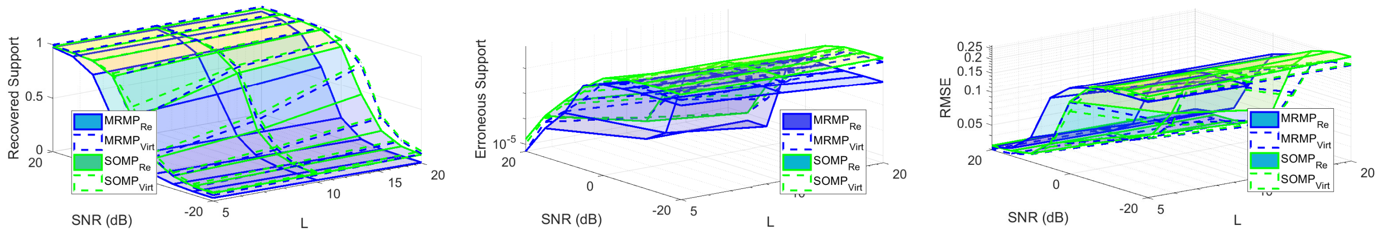
where $\sim$ eye(L) denotes the logical negation of the $L \times L$ identity matrix, averaging off-diagonal contributions. This transformation improves detection accuracy by exploiting inter-user correlations. The MRMP algorithm, detailed in Algorithm 1, introduces key enhancements over RMP and SOMP:

- *Correlation per channel:* The correlation is first normalized for each channel and then sorted to account for SNR variations and fading effects.
- *Selecting Only the Top-K Proxies:* To enhance efficiency, only the K highest correlation values are sorted instead of N values using the `kmax` MATLAB function.
- *Adaptive Support Selection*: MRMP dynamically updates the support set by selecting a batch of s atoms per iteration, reducing iterations from K to $I = \lceil K/s \rceil$.
- *VDS*: The use of $\tilde{\mathbf{Y}}$ boosts SNR, enhancing robustness against noise.
- *Reduced Complexity*: By pruning the search space with parameters b and a, MRMP maintains high performance with lower computational cost.
- *Joint Support estimation:* where the support selection is processed once for all users instead of doing it separately.

TABLE I: Complexity Comparison of MRMP, SOMP [7], and RMP [10].

Step	**MRMP** ($Y : M \times L$)	**SOMP** ($Y : M \times L$)	**RMP** ($Y : M \times 1$)
Initialization	$O(MN + ML)$	$O(MN + ML)$	$O(MN)$
Correlation	$O(MNL)$	$O(MNL)$	$O(MN)$
Normalization / Selection	$O(NL)$	$O(NL)$	$O(N)$
Support Update	$O(s)$	$O(NL)$	$O(s)$
Least Squares	$O(Mk^2 + MkL)$	$O(Mk^2 + MkL)$	$O(Mk^2 + Mk)$
Sparsity Enforcement	$O(NL + KL)$	$O(1)$ (implicit stop)	$O(N + K)$
Residual Update	$O(MNL)$	$O(MkL)$	$O(MN)$
Convergence Check	$O(ML)$	$O(ML)$	$O(M)$
Iterations	$I = \lceil K/s \rceil$	K	$I = \lceil K/s \rceil$
Total Complexity	$O\left(I(MNL + Mk^2 + MkL)\right)$	$O\left(K(MNL + Mk^2 + MkL)\right)$	$O\left(I(MN + Mk^2 + Mk)\right)$

Notes: N: number of atoms; M: number of measurements; L: number of users; K: sparsity level; k: support size; s: increment step in MRMP/RMP.



(a) Q_d Simulation for modulated signals. (b) Q_f Simulation for modulated signals. (c) RMSE Simulation for modulated signals.

Fig. 1: Performance comparison of MRMP and SOMP fed by real and transformed data for Q_d, Q_f, and RMSE metrics according to SNR and network size.

The use of multiple atom selection in MRMP accelerates convergence by updating several support indices simultaneously in each iteration? where grouping updates has been shown to significantly reduce the total number of iterations. In MRMP, we extend this idea by processing the signal proxy of each user independently, then performing a unified support update across all users. This not only reduces the iteration count but also allows the support to be computed once globally rather than separately for each of the L users, resulting in both computational and convergence efficiency.

A complexity comparison with SOMP [7] and RMP [10], shown in Table I, underscores MRMP's efficiency. Unlike RMP, which processes a single signal ($y : M \times 1$) with complexity $O(IMNL + IMLk^2 + IMkL)$, MRMP handles L users ($Y : M \times L$) in $O(IMNL + IMk^2 + IMkL)$, avoiding L-fold RMP executions. Compared to SOMP, MRMP reduces iterations from K (e.g., 68) to $I = \lceil K/s \rceil$ (e.g., 4–24) by selecting s atoms per iteration, cutting the dominant $O(MNL)$ term from $O(KMNL)$ to $O(IMNL)$. This yields:

- Comparable recovery performance to SOMP with lower complexity.
- Fast convergence via multiple atom selection.
- Scalability for larger networks with minimal overhead.

Thus, the MRMP algorithm emerges as an effective solution for JSR, offering a favorable trade-off between accuracy and efficiency. The sparsity level K plays a critical role in the performance of MRMP and is typically chosen based on prior knowledge of signal characteristics or determined empirically through cross-validation.

In future work, adaptive approaches—such as dynamic support growth or residual-based stopping criteria—could be investigated to further optimize the selection of K in real-time scenarios. According to the findings in [13], the sparsity level for the considered application is estimated not to exceed 6% of the signal dimension, providing a practical upper bound for algorithm configuration.

IV. Simulation Results

We compare the performance of MRMP with that of SOMP [7]. To enhance the SNR of the measurements, we apply the VDS technique, represented by intermittent lines in Figure 1. This figure analyzes performance using three key metrics: Q_d, Q_f, and Root Mean Square Error (RMSE). In all plots, SOMP results are shown in green, while MRMP results appear in blue. Solid lines represent real data.

Figure 1a illustrates the improvement in Q_d when MRMP is combined with VDS. As the network size and SNR increase, MRMP, represented by the blue intermittent 3D curve, progressively reaches the performance of SOMP. This demonstrates that integrating VDS allows MRMP to achieve a comparable detection probability to SOMP across all network sizes and SNR levels.

Figure 1b presents the evolution of Q_f with respect to SNR and the number of cooperating users (L). The lowest false alarm rate is achieved when MRMP processes real data directly from physical channels, although this configuration does not maximize the detection probability. However, when MRMP is fed with transformed data via VDS, it achieves a Q_d similar result to that of SOMP, regardless of whether SOMP operates on real or transformed data.

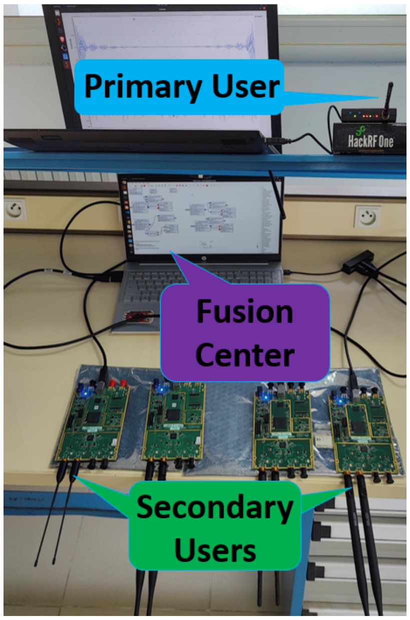


Fig. 2: Multi-User SDR Testbed for Joint Sparse Recovery.

Figure 1c highlights the superiority of MRMP over SOMP in terms of RMSE under all signal conditions and cooperation scenarios. In particular, the RMSE is lower bound at $RMSE_{\min} = 0.03$, a consequence of greedy algorithms prioritizing high-amplitude components while disregarding the noise floor.

Overall, these results confirm that MRMP, when combined with VDS, delivers detection performance on par with SOMP while significantly reducing computational complexity. Specifically, for L=20 users, MRMP requires just **40.82%** of the computational resources used by SOMP, making it a highly efficient alternative. Moreover, compared to separate RMP recovery, MRMP demands only **4.35%** of the resources, yet achieves nearly the same Q_d and Q_f values—further underscoring its effectiveness.

V. SDR Validation

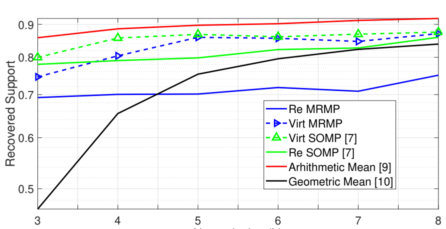
To validate the proposed MRMP algorithm in a real-world scenario, we implemented it using a Software-Defined Radio (SDR) testbed. The setup of Figure 2 consists of four USRP B210 devices acting as secondary users (SUs), each handling two independent channels, resulting in a total of eight sensing channels. A HackRF One serves as the primary user, transmitting a sparse Linear Frequency Modulated (LFM) and Non Linear Frequency Modulated (NLFM) signal, each occupying a separate frequency band within the monitored spectrum.

The SDRs are configured to operate within a cooperative compressed sensing (CCS) framework, where joint sparse recovery is performed using both the MRMP and SOMP algorithms. Signal reconstruction is performed on real data acquired directly from physical channels as well as on transformed compressed measurements processed through the VDS technique, which enhances SNR prior to recovery.

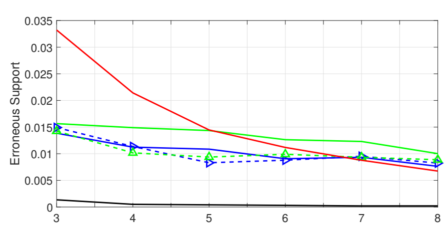
The cooperative RMP-based recovery approach, which involves independently reconstructing spectra before fusing them for decision-making, achieves exceptional results. Specifically, it maximizes Q_d (depicted in red in Figure 3a), while minimizing Q_f (black line in Figure 3b) and RMSE (Figure 3c). However, these performance gains come at the cost of increased computational complexity.

The experimental results in Figure 3 confirm the effectiveness of MRMP in practical conditions for network sizes ranging from 3 to 8 SU. MRMP was compared to SOMP and cooperative RMP using the geometric and arithmetic means [12], [13] as fusion rules. The detection probability (Q_d) closely follows simulation results, demonstrating a significant improvement when VDS is applied on both algorithms, as shown in Figure 3a (blue intermittent lines are over the solid lines of both MRMP and SOMP). MRMP approaches SOMP when combined to VDS. The small gap comes from the SNR instability between the channels, which was not considered in simulations.

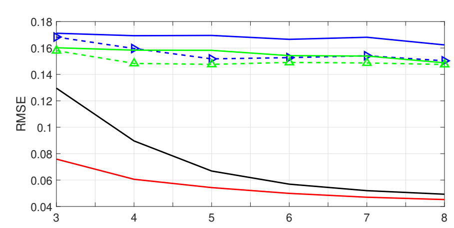
Figure 3b exhibits almost the lowest Q_f for MRMP fed by transformed data, which confirms the simulation results. Furthermore, the RMSE measurements in Figure 3c indicate that MRMP achieves low reconstruction error, consistently outperforming SOMP in terms of computational efficiency. The cooperative RMP employing arithmetic and geometric fusion rules achieves lower RMSE but at the cost of increased complexity. These findings validate the feasibility of MRMP for real-time compressed sensing applications using SDR hardware. Figure 4 illustrates the superposition of recovered spectra using MRPM and SOMP, alongside the original spectrum transmitted via HackRF One at $SNR = 0$ dB with



(a) SDR Validation of Q_d for modulated signals.



(b) SDR Validation of Q_f for modulated signals.



(c) SDR Validation of RMSE for modulated signals.

Fig. 3: SDR validation of MRMP and SOMP fed by real and transformed data for Q_d, Q_f, and RMSE metrics.

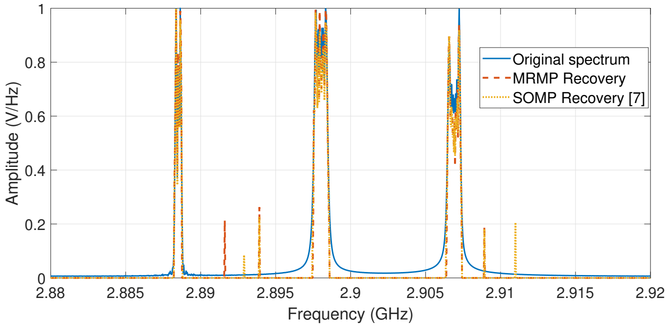


Fig. 4: Comparison of Spectrum Recovery Methods

$L = 20$ secondary users. Most recovered bins align with the occupied frequency bands, leading to an increase in Q_d. Missed detections manifest as bins leaking outside these bands, contributing to Q_f. Erroneous bins are minimal, scattered, and vary across techniques. Notably, the absence of a noise floor and the continuity of the recovered spectrum highlight a key characteristic of greedy algorithms: they estimate only the most significant bins while setting the rest to zero. As SNR and/or L increase, the recovered bins become more concentrated within the active sub-bands, enhancing detection accuracy.

VI. Future Works

While the proposed MRMP approach combined with VDS has demonstrated significant improvements in detection performance and computational efficiency, several avenues remain open for future exploration:

- **Adaptive User Selection:** Investigating dynamic user selection strategies based on real-time SNR estimation to further optimize cooperative sensing.
- **Machine Learning Integration:** Exploring deep learning models to refine sparse recovery techniques and improve detection in non-stationary environments.
- **Hardware Implementation:** Implementing MRMP on FPGA or GPU architectures to assess real-time feasibility and energy efficiency in SDR-based networks.
- **Extended Signal Models:** Extending the approach to handle non-linear distortions and wideband spectrum sensing scenarios.
- **Theoretical Performance Bounds:** Deriving analytical bounds on the detection probability and false alarm rate under different noise and sparsity conditions.

VII. Conclusion

This work introduced an enhanced CCS framework leveraging the MRMP algorithm in conjunction with a VDS technique. The proposed method significantly reduces computational complexity while maintaining detection performance comparable to traditional JSR techniques such as SOMP. Specifically, MRMP achieves a speedup of approximately **2.5 times** over SOMP and **23 times** over separate RMP executions, requiring only **4.35%** of the computational resources of separate RMP recoveries.

Experimental results on real-world SDR-acquired data confirm the effectiveness of MRMP, demonstrating superior detection performance while drastically reducing processing time. The integration of VDS further enhances SNR, improving the robustness of the spectrum sensing framework. These findings highlight the potential of MRMP as a scalable and efficient alternative for CCS in cognitive radio networks. The MRMP algorithm is particularly suited for practical deployment in real-time spectrum monitoring systems due to its low computational overhead. Potential applications include cognitive radio networks, dynamic spectrum sharing frameworks, and lightweight spectrum sensing in IoT systems where energy and speed constraints are critical. Future work will focus on adaptive user selection, deep learning-based enhancements, and hardware implementations to further refine and deploy the proposed approach in real-world applications.

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