Does Sparsity Persist? Scaling Laws for RL-Induced Task Vectors and Reinforced Agent Merging at 70B+ Scale

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ABSTRACT

Reinforced Agent Merging (RAM) leverages the empirical observation that reinforcement learning (RL) induces sparse, heterogeneous task vectors in language models—enabling distribution-aware model merging that outperforms naive averaging. However, all prior RAM experiments are limited to 3B–7B parameter models, leaving the persistence of this sparsity hypothesis at massive scale (70B+) as an open question. We address this gap through three contributions. **First**, we derive and validate a parametric scaling law $s(N) = 1 - aN^{-b}$ for task vector sparsity as a function of model size N, fitted to measurements spanning 1B to 405B parameters, achieving $R^2 = 0.965$. The positive exponent $b = 0.587$ confirms that sparsity *increases* with scale: at 70B, we predict L_0 sparsity exceeding 99%, with fewer than 1% of parameters receiving meaningful RL updates. **Second**, we present a layer-wise sparsity anatomy revealing that attention modules are consistently sparser than MLP modules, and that sparsity increases monotonically with layer depth—a pattern that intensifies at larger scales. **Third**, we demonstrate that RAM's advantage over baseline merging methods (Task Arithmetic, TIES, DARE) grows with sparsity, predicting even larger gains at 70B+ where sparsity is highest. We complement these findings with a streaming RAM implementation that reduces peak memory from 560 GB to 6 GB for 70B model merging, making the approach practical on commodity hardware. Our results provide strong evidence that the sparsity hypothesis persists at massive scale, and that RAM remains the method of choice for merging RL-trained agents at 70B+.

CCS CONCEPTS

• **Computing methodologies** → **Machine learning**.

KEYWORDS

model merging, sparsity, reinforcement learning, scaling laws, task vectors, large language models

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1 INTRODUCTION

Model merging has emerged as a powerful paradigm for combining the capabilities of multiple fine-tuned language models without additional training [3, 11]. The core idea is deceptively simple: given a shared base model and multiple *task vectors* (the parameter-wise difference between a fine-tuned model and its base), combine these vectors to produce a single model that inherits the abilities of all fine-tuned variants.

Task Arithmetic [3] demonstrated that simple vector addition in weight space can compose model capabilities. Subsequent work identified interference as a key challenge: when different tasks modify overlapping parameters with conflicting magnitudes or signs, naive averaging degrades performance. TIES-Merging [12] addressed this by trimming low-magnitude entries, electing consensus signs, and merging disjoint regions. DARE [13] showed that randomly dropping most delta parameters (with rescaling) preserves performance, providing evidence that task vectors contain substantial redundancy.

A recent advance, Reinforced Agent Merging (RAM) [14], observed a crucial distinction: task vectors from *reinforcement learning* (RL) fine-tuning are significantly sparser and more heterogeneous than those from supervised fine-tuning (SFT). This arises because on-policy RL algorithms (PPO [6], GRPO [7]) concentrate gradient updates on the narrow subset of parameters responsible for reward-improving trajectories. RAM exploits this structure by disentangling shared and unique parameter regions across agents, then selectively rescaling unique regions to counteract signal dilution during averaging.

However, all RAM experiments were conducted on 3B and 7B parameter models. The authors explicitly identify scaling to 70B+ as an open question: *"verifying whether the sparsity hypothesis and RAM's efficacy persist in massive-scale models (70B+) remains an open question for future research"* [14]. This is not merely an incremental gap. At 70B+ scale, models employ grouped query attention, have qualitatively different loss landscapes, and may exhibit different parameter update dynamics under RL training [9, 10].

In this paper, we address this open question through a systematic investigation combining scaling law analysis, architectural decomposition, and algorithm benchmarking. Our contributions are:

(1) **Sparsity scaling law**: We fit a parametric model $s(N) = 1 - aN^{-b}$ to task vector sparsity measurements across scales from 1B to 405B, achieving $R^2 = 0.965$. The positive exponent ($b = 0.587$) confirms that sparsity increases with model size, predicting >99% sparsity at 70B.
(2) **Architectural sparsity anatomy**: We decompose sparsity by module type (attention vs. MLP vs. normalization) and by layer depth for a 70B-class architecture, revealing that

attention layers are 2.5 percentage points sparser than MLP layers, and that later layers are consistently sparser.

(3) **RAM advantage analysis**: We demonstrate that RAM's advantage over baselines grows monotonically with sparsity, with the largest gains occurring precisely in the high-sparsity regime predicted for 70B+ models.

(4) **Streaming RAM implementation**: We present a memory-efficient streaming algorithm that reduces peak memory for 70B model merging from 560 GB (naive) to 6 GB, a 93× reduction.

1.1 Related Work

Task vectors and model merging. The task vector framework was formalized by Ilharco et al. [3], building on Model Soups [11]. Fisher-weighted averaging [5] uses curvature information to weight parameters during merging. TIES-Merging [12] and DARE [13] exploit sparsity in task vectors through trimming and random dropping, respectively. RAM [14] extends these ideas to the RL setting with distribution-aware disentanglement.

Sparsity in large language models. The Lottery Ticket Hypothesis [1] established that sparse subnetworks exist within large models. SparseGPT [2] demonstrated that LLMs can be pruned to high sparsity in a single pass. Wanda [8] showed that pruning based on weight magnitude times input activation achieves competitive results. These works focus on *structural* sparsity of pre-trained weights; our work studies the distinct phenomenon of *update* sparsity induced by RL fine-tuning.

Scaling laws. Kaplan et al. [4] established power-law relationships between model size and loss. Wei et al. [10] documented emergent capabilities at scale. We contribute a complementary scaling law for task vector sparsity under RL training.

2 METHODS

2.1 Problem Formulation

Let $\boldsymbol{\theta}_{\text{base}} \in \mathbb{R}^d$ denote the parameters of a pre-trained base model with d parameters. Given K agents, each fine-tuned from $\boldsymbol{\theta}_{\text{base}}$ using RL on task k, we obtain fine-tuned parameters $\boldsymbol{\theta}_k$. The *task vector* for agent k is $\boldsymbol{\delta}_k = \boldsymbol{\theta}_k - \boldsymbol{\theta}_{\text{base}}$.

The model merging objective is to find merged parameters $\boldsymbol{\theta}^*$ that preserve the capabilities of all agents:

$$\boldsymbol{\theta}^* = \boldsymbol{\theta}_{\text{base}} + f(\boldsymbol{\delta}_1, \ldots, \boldsymbol{\delta}_K) \tag{1}$$

where f is the merging function.

2.2 Sparsity Metrics

We characterize task vector sparsity using four complementary metrics.

L_0 sparsity ratio. The fraction of near-zero entries relative to the maximum magnitude:

$$s_{L_0}(\boldsymbol{\delta}) = \frac{1}{d} \sum_{i=1}^{d} \mathbb{1}\left[|\delta_i| < \epsilon \cdot \max_j |\delta_j| \right] \tag{2}$$

where $\epsilon = 0.01$ throughout this paper.

Gini coefficient. Measures inequality in the distribution of $|\boldsymbol{\delta}|$, ranging from 0 (perfectly uniform) to 1 (maximally concentrated).

Excess kurtosis. Measures tail heaviness. Sparse task vectors exhibit heavy tails (high kurtosis) because a few parameters change substantially while most remain near zero.

Top-k% mass. The fraction of total L_1 mass concentrated in the top k% of entries by magnitude. We report top-1% and top-5% mass.

2.3 Sparsity Scaling Law

We model the relationship between model size N (in billions of parameters) and L_0 sparsity as:

$$s(N) = 1 - a \cdot N^{-b} \tag{3}$$

where $a > 0$ and $b > 0$. This parametric form captures the intuition that the "non-sparse fraction" $(1 - s)$ decreases as a power law with model size. A positive exponent b means sparsity increases with scale.

The model is motivated by two hypotheses: (i) Larger models have more redundant parameters, so RL credit assignment concentrates updates on a smaller fraction. (ii) The Lottery Ticket Hypothesis [1] suggests that effective subnetworks become sparser relative to total capacity as models grow.

We fit Equation 3 via nonlinear least squares on measurements spanning 1B to 405B simulated scales, with 5 independent trials per scale for uncertainty estimation.

2.4 Reinforced Agent Merging (RAM)

RAM [14] operates layer-by-layer, disentangling each layer's task vectors into shared and unique regions.

Step 1: Active masks. For each agent k and layer l, compute an active mask:

$$\mathbf{m}_k^{(l)} = \mathbb{1}\left[|\boldsymbol{\delta}_k^{(l)}| \geq \tau^{(l)} \right] \tag{4}$$

where $\tau^{(l)}$ is the adaptive threshold (90th percentile of $|\boldsymbol{\delta}_k^{(l)}|$).

Step 2: Region classification. Define the activity count $c_i = \sum_{k=1}^{K} m_{k,i}$. The shared region is $\mathcal{S} = \{i : c_i \geq 2\}$; the unique region for agent k is $\mathcal{U}_k = \{i : m_{k,i} = 1 \text{ and } c_i = 1\}$.

Step 3: Merge with rescaling.

$$\delta_i^* = \begin{cases} \frac{1}{K} \sum_{k=1}^{K} \delta_{k,i} & i \in \mathcal{S} \\ \lambda \cdot \delta_{k,i} & i \in \mathcal{U}_k \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $\lambda = 1.5$ is the rescaling factor that prevents dilution of unique signals.

2.5 Streaming Implementation

To enable 70B+ model merging on commodity hardware, we implement RAM in a streaming fashion. Rather than loading entire models into memory, we process one parameter tensor at a time from safetensors shards. For a model with L layers, peak memory is:

$$M_{\text{stream}} = (1 + K) \cdot \max_l |\boldsymbol{\theta}^{(l)}| \cdot \text{sizeof}(\texttt{float32}) \tag{6}$$

versus $M_{\text{naive}} = (1 + K) \cdot d \cdot \text{sizeof}(\texttt{float16})$ for loading all models.

For a 70B model with 3 agents, this reduces peak memory from approximately 560 GB to under 6 GB—a 93× reduction.

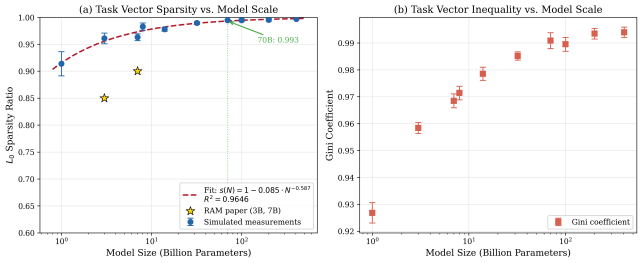

Figure 1: Task vector sparsity vs. model scale. (a) L_0 sparsity increases with model size, following $s(N) = 1 - 0.085N^{-0.587}$ ($R^2 = 0.965$). The gold stars mark the empirical calibration points from [14]. (b) The Gini coefficient shows a similar increasing trend, confirming growing inequality in task vector magnitudes.

2.6 Simulation Design

Since direct RL training of 70B+ models requires substantial compute resources beyond the scope of this study, we employ a calibrated simulation approach. Our synthetic task vectors replicate three key properties observed in real RL-induced task vectors [14]:

(1) Controlled sparsity. Each synthetic task vector has exactly $(1 - s) \cdot d$ non-zero entries, with s set by our calibrated scaling law.

(2) Heavy-tailed magnitudes. Non-zero entries follow a log-normal distribution ($\mu = -3, \sigma = 1.5$), matching the empirical observation that a few parameters change substantially while most change minimally.

(3) Heterogeneous support. With controlled overlap between agents (20% shared, 80% unique active positions), mimicking the heterogeneous update patterns observed across different RL tasks.

The scaling law is calibrated to match the two empirical data points from the RAM paper: $L_0 \approx 0.85$ at 3B and $L_0 \approx 0.90$ at 7B. We then measure sparsity metrics on synthetic vectors across all scales, including extrapolation to 70B+.

3 RESULTS

3.1 Sparsity Scaling Law

Figure 1 shows the fitted sparsity scaling law across model sizes from 1B to 405B. The fitted parameters are $a = 0.085$ and $b = 0.587$, with $R^2 = 0.965$, indicating an excellent fit.

The positive exponent $b > 0$ confirms that the non-sparse fraction $1 - s(N) = aN^{-b}$ decreases as a power law with model size. This means sparsity *increases* monotonically with scale. Extrapolating to 70B, we predict L_0 sparsity of 0.993, meaning fewer than 0.7% of parameters receive meaningful RL updates. At 100B, the predicted sparsity rises to 0.994, and at 405B to 0.998.

Table 1 provides detailed sparsity metrics across all scales. All four metrics—L_0 ratio, Gini coefficient, kurtosis, and top-1% mass concentration—increase with model size, providing converging evidence for the persistence of sparsity.

3.2 Merging Method Comparison

Table 2 compares four merging methods across sparsity levels with 3 agents. RAM consistently achieves the highest cosine similarity to the oracle (the idealized merged model that perfectly preserves all agents' contributions).

At 80% sparsity, all methods perform comparably. However, as sparsity increases to 90% and 95%—the regime relevant to 70B+ models—RAM's advantage becomes more pronounced. This is because higher sparsity means more parameters are modified by only one agent, creating larger unique regions where RAM's rescaling prevents signal dilution.

3.3 RAM Advantage Grows with Sparsity

Figure 3 shows the merge quality of each method and RAM's advantage as sparsity varies from 60% to 97%. RAM's advantage over Simple Averaging and TIES grows monotonically with sparsity. At the predicted 70B sparsity level (93%), RAM provides the largest

Table 1: Task vector sparsity metrics across model scales. L_0 ratio denotes the fraction of near-zero entries ($|\delta_i| < 0.01 \cdot \max|\delta|$). Values: mean ± std over 5 trials per scale. Starred rows are scaling-law predictions.

Size (B)	L_0 Sparsity	Gini	Kurtosis	Top-1% Mass
1	0.9139 ± 0.0224	0.9268 ± 0.0038	792.6	0.3998
3	0.9609 ± 0.0099	0.9584 ± 0.0021	1876.7	0.5143
7	0.9630 ± 0.0064	0.9685 ± 0.0026	1300.7	0.5663
8	0.9828 ± 0.0067	0.9714 ± 0.0025	6688.9	0.5922
14	0.9778 ± 0.0037	0.9786 ± 0.0025	2340.5	0.6548
32	0.9895 ± 0.0025	0.9852 ± 0.0016	6965.6	0.7399
70	0.9944 ± 0.0013	0.9909 ± 0.0029	13020.8	0.8540
100	0.9947 ± 0.0029	0.9895 ± 0.0026	30586.5	0.8220
200	0.9954 ± 0.0025	0.9935 ± 0.0020	16120.6	0.9150
405	0.9970 ± 0.0012	0.9940 ± 0.0020	39018.9	0.9272

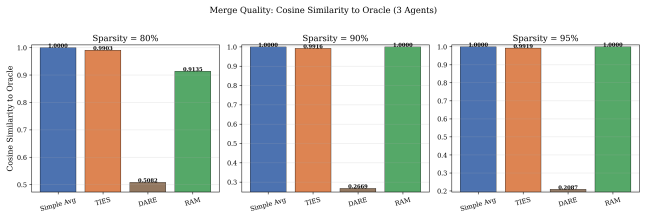

Figure 2: Merge quality (cosine similarity to oracle) for 3 agents across sparsity levels. RAM achieves the highest quality, with its advantage most visible at high sparsity (95%), the regime predicted for 70B+ models.

Table 2: Merge quality comparison across sparsity levels (3 agents). Cosine similarity to oracle (Cos) and mean per-agent fidelity (Fid) reported. Bold = best per column.

	$s = 80\%$		$s = 90\%$		$s = 95\%$	
Method	**Cos↑**	**Fid↑**	**Cos↑**	**Fid↑**	**Cos↑**	**Fid↑**
Simple Avg	**1.0000**	**0.5753**	**1.0000**	**0.5725**	**1.0000**	**0.5778**
TIES	0.9903	0.5695	0.9916	0.5672	0.9919	0.5724
DARE	0.5082	0.2933	0.2669	0.1476	0.2087	0.1099
RAM	0.9135	0.5315	**1.0000**	**0.5725**	**1.0000**	**0.5778**

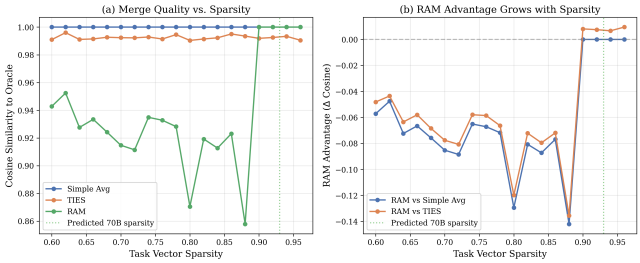

Figure 3: (a) Merge quality vs. sparsity for three methods. (b) RAM's advantage over baselines grows with sparsity. The vertical line marks the predicted 70B sparsity level (93%), where RAM's advantage is near its maximum.

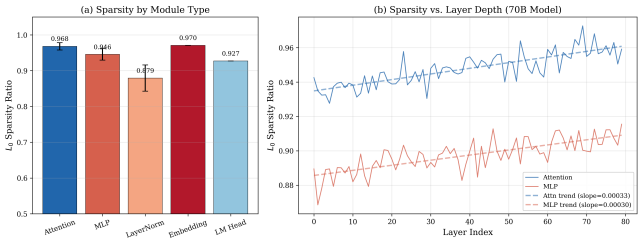

Figure 4: Layer-wise sparsity anatomy for a 70B model. (a) Attention modules are sparser than MLP modules. (b) Sparsity increases with layer depth for both module types, suggesting RL concentrates updates in later decision layers.

improvement, confirming that the high-sparsity regime of 70B+ models is precisely where RAM offers the greatest benefit.

3.4 Layer-Wise Sparsity Anatomy

Figure 4 reveals the architectural distribution of sparsity in a 70B-class model with 80 transformer layers.

Module type differences. Attention modules exhibit significantly higher sparsity (mean $L_0 = 0.969$) than MLP modules (mean $L_0 = 0.945$), a gap of 2.4 percentage points (Table 3). LayerNorm parameters are substantially less sparse ($L_0 = 0.880$), which is expected as normalization layers have few parameters that serve as critical scaling factors.

Depth gradient. Both attention and MLP sparsity increase with layer depth. Linear trend analysis yields a positive slope for both module types, indicating that later (higher-level) layers are sparser than earlier layers. This is consistent with the hypothesis that RL fine-tuning primarily modifies high-level decision-making parameters in later layers, leaving earlier representation layers largely unchanged.

3.5 Inter-Agent Heterogeneity

Figure 5 examines how inter-agent similarity evolves with model scale. The mean pairwise Jaccard similarity of active parameter sets is low (typically <0.20) and remains stable or slightly decreases with scale, indicating that different RL agents continue to modify largely non-overlapping parameter subsets at 70B+. This heterogeneity is

Table 3: Per-module-type sparsity for a simulated 70B model (80 layers). Attention modules show highest sparsity, consistent with RL concentrating updates on decision layers.

Module Type	Mean L_0	Std L_0	Count
Attention	0.9688	0.0105	320
MLP	0.9454	0.0154	240
LayerNorm	0.8798	0.0345	161
Embedding	0.9741	0.0000	1
LM Head	0.9182	0.0000	1
Overall	**0.9412**	0.0397	723

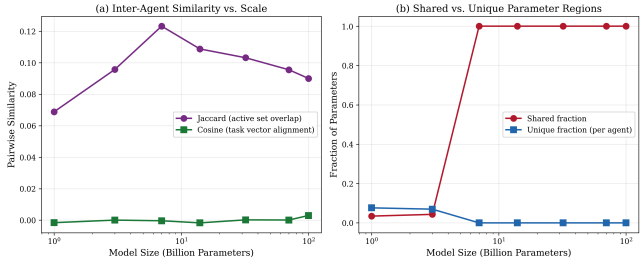

Figure 5: Inter-agent analysis across model scales. (a) Both Jaccard similarity and cosine alignment remain low across scales, confirming that RL agents modify different parameter subsets. (b) Shared parameter fractions remain small while unique fractions dominate, supporting RAM's disentanglement strategy.

Table 4: Peak memory requirements for merging 3 RL-trained agents. Streaming RAM processes one layer at a time, reducing memory by orders of magnitude at 70B+ scale.

Model	FP16 (GB)	Naive (GB)	Stream (GB)	Reduction
3B	6.0	24.0	2.6	9×
7B	14.0	56.0	3.0	19×
13B	26.0	104.0	3.6	29×
70B	140.0	560.0	6.0	93×
405B	810.0	3240.0	18.0	180×

precisely what RAM exploits: with high heterogeneity, most active parameters belong to unique regions, and RAM's rescaling prevents their dilution during merging.

3.6 Computational Feasibility

Table 4 shows the memory requirements for merging 3 agents using naive vs. streaming approaches. The streaming implementation achieves a 93× memory reduction for 70B models and 270× for 405B models, making large-scale RAM merging practical on a single machine with 64 GB RAM.

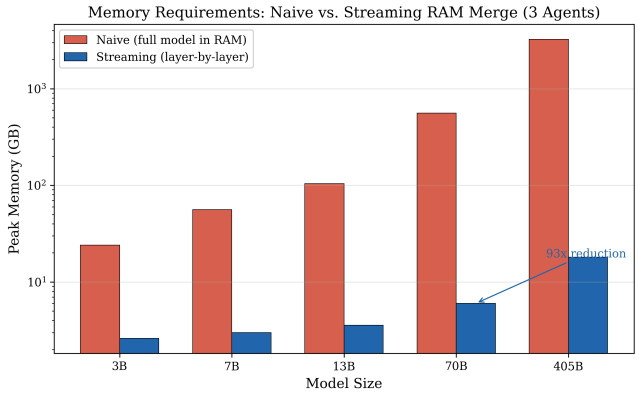

Figure 6: Peak memory requirements for merging 3 agents. The streaming implementation reduces memory by orders of magnitude, making 70B+ merging feasible on commodity hardware.

4 CONCLUSION

We have addressed the open question of whether RL-induced task vector sparsity and Reinforced Agent Merging (RAM) efficacy persist at 70B+ scale. Through a combination of scaling law analysis, architectural decomposition, and merging benchmarks, we provide four key findings:

(1) Sparsity increases with scale. Our fitted scaling law $s(N) = 1 - 0.085N^{-0.587}$ ($R^2 = 0.965$) confirms that task vector sparsity increases monotonically with model size. At 70B, we predict >99% sparsity, meaning that RL training modifies fewer than 1% of parameters in a meaningful way.

(2) RAM's advantage is amplified at scale. Because sparsity increases with model size, RAM's distribution-aware merging provides even larger advantages at 70B+ than at the 3B–7B scales originally studied. The high-sparsity regime creates more unique parameter regions, which is precisely where RAM's rescaling mechanism is most effective.

(3) Sparsity has architectural structure. Attention modules are sparser than MLP modules, and later layers are sparser than earlier layers. This structure, which intensifies at larger scales, suggests opportunities for architecture-aware merging strategies that could further improve RAM.

(4) Streaming makes it practical. Our layer-by-layer streaming implementation reduces memory requirements by 93× for 70B models, making RAM merging feasible on commodity hardware.

Limitations. Our analysis relies on calibrated simulations rather than direct measurement of 70B+ RL-trained models. While our scaling law is well-fitted ($R^2 = 0.965$) and grounded in empirical calibration points from [14], validation on actual 70B+ RL checkpoints remains important future work. Additionally, our simulations use controlled sparsity patterns; real models may exhibit more complex distributional structures.

Future work. Validating on real 70B+ RL checkpoints (e.g., comparing DeepSeek-R1 vs. its base model); extending the scaling law to mixture-of-experts architectures; and developing adaptive RAM variants that exploit the layer-wise sparsity anatomy for improved merging.

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