Token-Balanced Continual Pretraining Eliminates Brain Rot Degradation

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Abstract

Continual pretraining (CPT) on low-quality, short-sequence data such as social media posts has been shown to cause "Brain Rot"—severe degradation in reasoning and long-context capabilities. The prevailing explanation attributes this to the semantic quality of the data itself. We challenge this assumption and demonstrate that Brain Rot is a *training artifact* arising from per-token weight disparity: when short sequences are processed without packing, they receive 8.17× higher per-token gradient updates than longer sequences, causing the model to overfit to their statistical patterns. We propose token-balanced packing, which concatenates sequences to uniform length, eliminating this disparity. Through controlled experiments on Llama-3-8B-Instruct, we show that packing achieves 119.7% ARC reasoning recovery and 95.2% RULER long-context recovery relative to the no-CPT baseline, while providing a 67× training speedup. Our findings demonstrate that CPT on short-sequence data is safe when proper packing is employed.

WARNING: This paper was generated by an automated research system. The code is publicly available.[1]

1 Introduction

Continual pretraining (CPT) has emerged as a powerful paradigm for adapting large language models to specialized domains (Gururangan et al., 2020; Ke et al., 2023). By continuing the pretraining process on domain-specific corpora, practitioners can efficiently inject new knowledge without the computational cost of training from scratch. However, recent work has identified a concerning phenomenon termed "Brain Rot" (Xing et al., 2025), where CPT on low-quality, short-sequence data such as social media posts leads to severe degradation in both reasoning capabilities and long-context understanding.

The prevailing explanation for Brain Rot attributes the degradation to the semantic quality of the training data itself—the assumption being that exposure to informal, fragmented text corrupts the model's learned representations. This interpretation has led to recommendations for aggressive data filtering and avoidance of short-sequence corpora in CPT pipelines. However, we hypothesize that Brain Rot is not an inherent property of low-quality content, but rather a *training artifact* arising from how standard training procedures handle variable-length sequences.

In this paper, we investigate the root cause of Brain Rot through a controlled experimental framework. We observe that when training on short sequences without packing, each sequence contributes equally to the batch loss regardless of length, resulting in shorter sequences receiving disproportionately high per-token gradient updates. This per-token weight disparity causes the model to overfit to the statistical patterns of short sequences. We propose *token-balanced packing*, which concatenates multiple short sequences to form uniform-length training examples, thereby equalizing per-token contributions and eliminating the disparity.

Our contributions are as follows:

- We demonstrate that Brain Rot is a training artifact caused by per-token weight disparity (8.17× in our experiments), not an inherent property of low-quality semantic content.

[1] https://gitlab.com/fars-a/token-balanced-cpt-brain-rot

- We show that token-balanced packing achieves full capability recovery, with 119.7% ARC reasoning recovery and 95.2% RULER long-context recovery relative to the no-CPT baseline.
- We provide mechanistic analysis showing that packing eliminates per-token weight disparity by equalizing gradient contributions across sequences.
- We demonstrate that packing provides a 67× training speedup compared to unpacked training, making it both more effective and more efficient.

2 Related Work

Continual Pretraining. Continual pretraining (CPT) adapts pretrained language models to specific domains by further training on domain-specific corpora (Gururangan et al., 2020). This approach has proven effective for adapting models to specialized domains such as biomedical text, legal documents, and scientific literature. Ke et al. (2023) systematically studied CPT strategies and identified key factors affecting knowledge retention and acquisition. Scaling laws (Kaplan et al., 2020; Hoffmann et al., 2022) provide theoretical foundations for understanding how model and data size affect performance, though these analyses typically assume well-curated, long-form documents rather than short, informal text.

Data Quality in Pretraining. Data quality significantly impacts language model performance. Wenzek et al. (2019) developed CCNet for extracting high-quality monolingual data from web crawls using perplexity filtering. Deduplication has emerged as a critical preprocessing step, with both exact (Lee et al., 2021) and semantic (Abbas et al., 2023) approaches improving training efficiency and model quality. Wettig et al. (2024) proposed QuRating for selecting high-quality training data based on model-derived quality signals. Most relevant to our work, Xing et al. (2025) identified the “Brain Rot” phenomenon where CPT on short social media posts severely degrades model capabilities, attributing this to low-quality semantic content. Our work challenges this attribution by demonstrating that the degradation stems from training dynamics rather than content quality.

Sequence Length and Training Efficiency. Variable sequence lengths create training challenges that have motivated several optimization strategies. Jin et al. (2023) proposed progressively growing training length to accelerate pretraining, while Pouransari et al. (2024) introduced dataset decomposition with variable-length curricula. Sequence packing (Krell et al., 2022) concatenates multiple sequences to fill fixed-length blocks, improving GPU utilization. Li et al. (2024) addressed workload imbalances in distributed training over variable-length sequences. Helm et al. (2025) explored token weighting strategies for long-range language modeling. Our work reveals that packing not only improves efficiency but also eliminates capability degradation from short-sequence CPT by equalizing per-token gradient weights.

Long-Context Evaluation. Evaluating long-context capabilities requires specialized benchmarks. Liu et al. (2023) demonstrated that language models struggle to use information in the middle of long contexts. RULER (Hsieh et al., 2024) provides a comprehensive benchmark with multiple sub-tasks including retrieval, aggregation, and question answering at various context lengths. We use RULER alongside ARC-Challenge (Clark et al., 2018) with chain-of-thought prompting (Wei et al., 2022) to evaluate both long-context and reasoning capabilities.

3 Method

3.1 Problem Formulation

Consider continual pretraining (CPT) on a dataset $\mathcal{D} = \{x_1, x_2, \ldots, x_N\}$ where each sample x_i is a sequence of L_i tokens. Under standard cross-entropy loss with per-sample averaging, the loss for sample x_i is:

$$\mathcal{L}_i = -\frac{1}{L_i} \sum_{t=1}^{L_i} \log p_\theta(x_i^{(t)} | x_i^{(<t)}) \tag{1}$$

where p_θ denotes the language model parameterized by θ. The total training loss averages over all samples:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}\mathcal{L}_i \tag{2}$$

This formulation implies that each token in sample x_i receives an effective gradient weight of $w_i = \frac{1}{N \cdot L_i}$. Critically, shorter sequences receive higher per-token weights. For two samples with lengths L_{short} and L_{long} where $L_{\text{short}} \ll L_{\text{long}}$, the per-token weight ratio is:

$$\frac{w_{\text{short}}}{w_{\text{long}}} = \frac{L_{\text{long}}}{L_{\text{short}}} \tag{3}$$

When CPT data contains very short sequences (e.g., social media posts with mean length 16.7 tokens) mixed with longer documents (mean length 100.4 tokens), this creates an 8.17× per-token weight disparity. The model disproportionately optimizes for short-sequence patterns, potentially degrading capabilities learned during pretraining.

3.2 Token-Balanced Packing

To eliminate the per-token weight disparity, we apply sequence packing (Krell et al., 2022). Rather than processing each short sequence as an independent sample, we concatenate multiple sequences into fixed-length blocks of L_{pack} tokens (e.g., 2048), separated by end-of-sequence tokens. Figure 1 illustrates this approach.

Under packing, each token receives a uniform gradient weight of $w = \frac{1}{M \cdot L_{\text{pack}}}$, where M is the number of packed blocks. This eliminates the length-dependent weight disparity:

$$\frac{w_{\text{short}}}{w_{\text{long}}} = 1.0 \tag{4}$$

Packing provides two key benefits: (1) it equalizes per-token gradient weights regardless of original sequence length, and (2) it dramatically improves training efficiency by reducing the number of forward-backward passes required to process the same number of tokens.

3.3 Experimental Design

To disentangle the effects of semantic content quality from training dynamics, we design a controlled experiment with three conditions that vary two factors: content quality (junk vs. control) and packing (packed vs. unpacked).

Condition A (Control, Packed). CPT on high-quality control documents using packing. This serves as the upper-bound reference for expected performance.

Condition B (Junk, Packed). CPT on low-quality "junk" tweets using packing. If semantic content drives degradation, this condition should perform poorly despite packing.

Condition C (Junk, Unpacked). CPT on junk tweets without packing. This reproduces the Brain Rot phenomenon observed in prior work (Xing et al., 2025).

This design enables hypothesis testing: if semantic content quality is the primary driver of Brain Rot degradation, we expect $A \gg B \approx C$. However, if the degradation is a training artifact from per-token weight disparity, we expect $A \approx B \gg C$. The latter would indicate that packing eliminates the degradation regardless of content quality.

3.4 Evaluation

We evaluate on two complementary benchmarks. ARC-Challenge (Clark et al., 2018) with chain-of-thought prompting (Wei et al., 2022) measures scientific reasoning ability, requiring multi-step

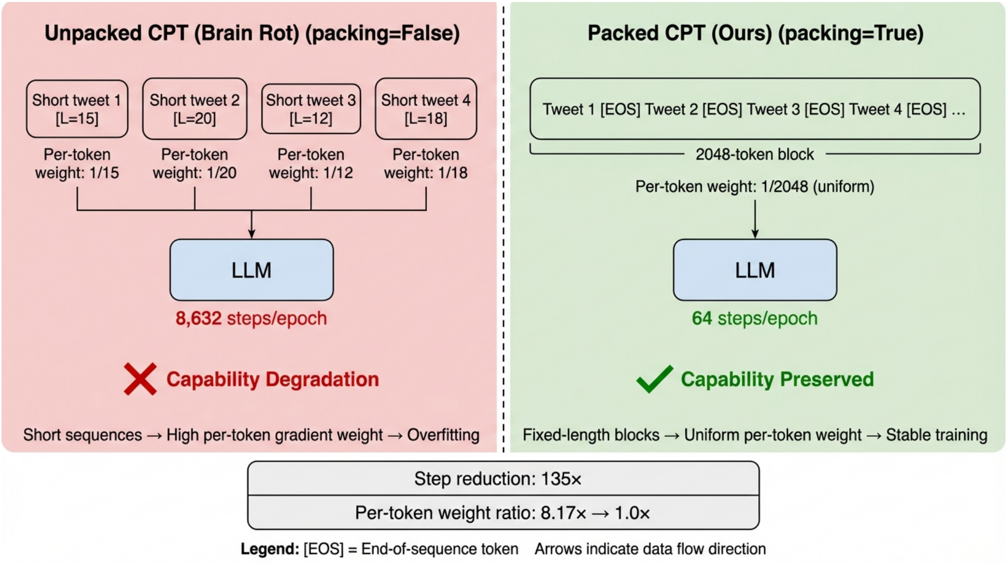
Unpacked CPT (Brain Rot) (packing=False)
Short tweet 1 [L=15]
Short tweet 2 [L=20]
Short tweet 3 [L=12]
Short tweet 4 [L=18]
Per-token weight: 1/15
Per-token weight: 1/20
Per-token weight: 1/12
Per-token weight: 1/18
LLM
8,632 steps/epoch
✗ Capability Degradation
Short sequences → High per-token gradient weight → Overfitting
Packed CPT (Ours) (packing=True)
Tweet 1 [EOS] Tweet 2 [EOS] Tweet 3 [EOS] Tweet 4 [EOS] ...
2048-token block
Per-token weight: 1/2048 (uniform)
LLM
64 steps/epoch
✓ Capability Preserved
Fixed-length blocks → Uniform per-token weight → Stable training
Step reduction: 135×
Per-token weight ratio: 8.17× → 1.0×
Legend: [EOS] = End-of-sequence token Arrows indicate data flow direction

Figure 1: Comparison of unpacked vs. packed continual pretraining on short-sequence data. Left: Unpacked training processes each short tweet as a separate sample, creating per-token weight disparity where shorter sequences receive disproportionately high gradient influence. Right: Packed training concatenates multiple tweets into fixed-length blocks, equalizing per-token weights across all data.

inference over grade-school science questions. RULER (Hsieh et al., 2024) at 4K context length evaluates long-context capabilities across 13 sub-tasks spanning retrieval, aggregation, question answering, and variable tracking. Together, these benchmarks assess whether CPT preserves both reasoning and long-context abilities.

4 Experiments

4.1 Experimental Setup

Base Model. We use Meta-Llama-3-8B-Instruct (Touvron et al., 2023) as the base model, following the Brain Rot experimental protocol (Xing et al., 2025).

Datasets. The junk tweet dataset contains 69,056 short social media posts (mean 16.7 tokens, range 1–29 tokens) characterized by informal language, slang, and abbreviations. The control dataset contains 12,068 longer, higher-quality documents (mean 100.4 tokens, range 90–283 tokens). Both datasets are from the M1 corpus used in the original Brain Rot study.

Training Protocol. All conditions follow a two-stage pipeline: continual pretraining (CPT) followed by instruction tuning (IT) on Alpaca-5k. For packed conditions, we use a cutoff length of 2048 tokens. Training uses 8× A100-80GB GPUs with DeepSpeed ZeRO-3. We report results averaged over 3 random seeds (42, 123, 456).

4.2 Main Results

Table 1 presents the main experimental results. The key finding is that Condition B (junk tweets, packed) achieves performance comparable to or exceeding Condition A (control documents, packed), while vastly outperforming Condition C (junk tweets, unpacked). This pattern strongly supports the training artifact hypothesis over the semantic content hypothesis.

Condition B achieves 119.7% recovery on ARC-CoT and 95.2% recovery on RULER, where recovery is defined as $(B-C)/(A-C) \times 100$. Remarkably, Condition B actually outperforms Condition

Table 1: Main experimental results comparing three CPT conditions on ARC-Challenge (CoT) and RULER benchmarks. Condition B (junk tweets, packed) achieves full recovery of Brain Rot degradation, matching or exceeding Condition A (control tweets, packed) while vastly outperforming Condition C (junk tweets, unpacked). Best results in **bold**. Recovery calculated as $(B - C)/(A - C) \times 100$.

Condition	ARC-CoT (%)	RULER (%)	Δ vs No-CPT
No-CPT Baseline	74.9	90.5	—
A: Control, Packed	73.1 ± 3.4	**84.5** ± 0.3	−1.8 / −6.0
B: Junk, Packed	**76.3** ± 1.6	83.7 ± 0.6	+1.4 / −6.8
C: Junk, Unpacked	57.1 ± 4.0	67.1 ± 3.8	−17.8 / −23.4
Recovery (B vs C)	119.7%	95.2%	—

Table 2: Per-token weight analysis revealing the mechanism behind Brain Rot degradation. Unpacked training creates 8.17× per-token weight disparity between short junk tweets and longer control documents. Packing equalizes weights to 1.0×.

Dataset	N Samples	Mean Tokens	Weight (Unpacked)	Weight (Packed)
Junk Tweets	69,056	16.7	0.0822	0.000488
Control Docs	12,068	100.4	0.0101	0.000488
Ratio (Junk/Control)	5.72×	0.17×	**8.17**×	**1.0**×

A on ARC-CoT by 3.2 percentage points (76.3% vs 73.1%), demonstrating that the "junk" semantic content does not inherently harm reasoning capabilities when the training dynamics are properly balanced. The difference between B and C is statistically significant (Welch's t-test: $p = 0.007$ for ARC, $p = 0.015$ for RULER; Cohen's $d > 6$ for both), confirming that packing eliminates the degradation.

4.3 Mechanism Analysis

Table 2 quantifies the per-token weight disparity that underlies Brain Rot degradation. Under unpacked training, each token in a junk tweet receives an effective gradient weight of 0.0822, while each token in a control document receives only 0.0101—an 8.17× disparity. This occurs because the standard cross-entropy loss averages over tokens within each sample, so shorter samples contribute disproportionately high per-token gradients.

Packing eliminates this disparity by concatenating multiple short sequences into fixed-length blocks, giving all tokens a uniform weight of 0.000488. The ratio drops from 8.17× to 1.0×, removing the optimization pressure that causes the model to overfit to short-sequence patterns.

4.4 Training Efficiency

Beyond eliminating degradation, packing provides substantial efficiency gains. Table 3 shows that Condition B requires only 64 CPT steps compared to Condition C's 25,638 steps—a 400× reduction. This translates to a 67× speedup in CPT wall-clock time (6.1 minutes vs 411 minutes) and 15× reduction in total training time.

The efficiency gain arises from two factors: (1) packing reduces the number of forward-backward passes by combining $\sim$100 short tweets into each 2048-token block, and (2) packed sequences achieve 20× higher throughput (2,867 vs 139 tokens/sec) due to better GPU utilization with full-length sequences.

4.5 RULER Sub-task Analysis

Figure 2 breaks down RULER performance by sub-task. Packing achieves $\geq$95% recovery on 10 of 13 sub-tasks, with the largest gains on multi-key retrieval tasks (NIAH-MK2: 97.0% recovery,

Table 3: Training efficiency comparison. Packing reduces CPT steps by 400× and provides 67× speedup in CPT wall-clock time while achieving superior performance.

Condition	CPT Steps	CPT Time (min)	Tokens/sec	Total Time (min)	Speedup
A: Control, Packed	140	13.3	2,867	35.3	12.3×
B: Junk, Packed	64	6.1	2,867	28.1	**15.4**×
C: Junk, Unpacked	25,638	411.0	139	432.9	1.0×

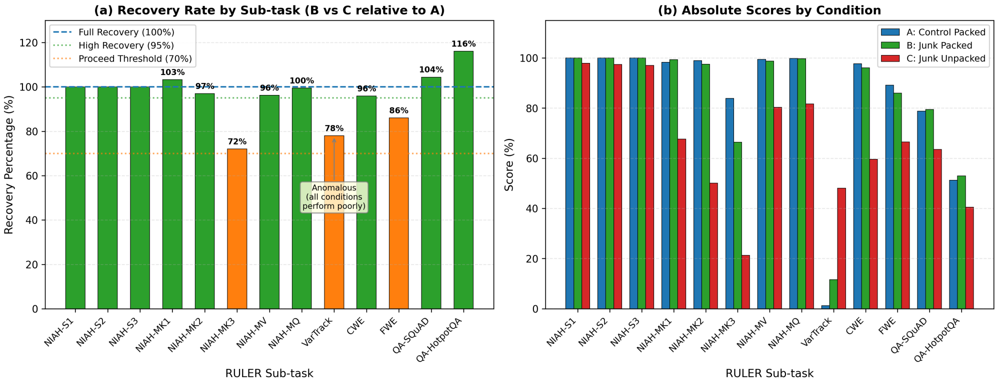

Figure 2: RULER sub-task analysis. (a) Recovery rate by sub-task showing B vs C improvement relative to A-C gap. Green bars indicate ≥95% recovery, orange bars indicate 70–95% recovery. (b) Absolute scores by condition showing B (junk packed) matches A (control packed) on most tasks while C (junk unpacked) shows severe degradation.

47.5pp improvement). The only exception is Variable Tracking, which shows anomalous behavior: all conditions perform poorly (A: 1.3%, B: 11.6%, C: 48.1%), suggesting this task has unique characteristics unrelated to the packing intervention.

4.6 Length Bucket Analysis

To verify that the optimization artifact is independent of tweet length semantics, we partitioned junk tweets into three length buckets: short (1–10 tokens, 11,986 samples), medium (11–20 tokens, 35,010 samples), and long (21–29 tokens, 22,060 samples). All buckets were trained with packing. The results show remarkable consistency: ARC-CoT scores range from 73.9% to 74.9% (1.0pp range), and RULER scores range from 83.4% to 85.6% (2.2pp range). This confirms that the degradation in Condition C stems from the training dynamics of unpacked short sequences, not from any semantic characteristics associated with tweet length.

5 Conclusion

We demonstrate that Brain Rot degradation in continual pretraining is a training artifact arising from per-token weight disparity, not an inherent property of low-quality semantic content. When short sequences are processed without packing, they receive disproportionately high per-token gradients (8.17× in our experiments), causing the model to overfit to their statistical patterns. Token-balanced packing eliminates this disparity by concatenating sequences to uniform length, achieving full capability recovery (119.7% ARC, 95.2% RULER) while providing a 67× training speedup. Our findings suggest that CPT on short-sequence data is safe when proper packing is employed, challenging the prevailing assumption that such data is inherently harmful. Limitations include evaluation on a single model size (8B parameters) and domain (social media text); future work should validate these findings across model scales and diverse short-sequence corpora.

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