Fine-Tuning Large Language Models for Marketing Content Generation: A Parameter-Efficient Approach

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Abstract

Large language models (LLMs) excel in natural language processing but often struggle with domain-specific tasks like marketing content generation due to their broad training. Traditional fine-tuning of such models requires substantial computational resources, exceeding standard hardware capabilities. This paper presents a resource-efficient framework for adapting the unsloth/Meta-Llama-3-8B-bnb-4bit model—a 4-bit quantized variant of Meta's Llama-3-8B—to generate marketing content. Utilizing Low-Rank Adaptation (LoRA) and 4-bit quantization, we minimize memory usage while optimizing performance on the RafaM97/marketing_social_media dataset from Hugging Face, comprising 689 instruction-response pairs for social media, email, and content marketing tasks. Our Python-based ecosystem—PyTorch, transformers, unsloth, and bitsandbytes—processes data, fine-tunes the model, and generates outputs like Instagram campaigns and email sequences. Training on a Tesla T4 GPU via Google Colab, we achieved a training loss reduction from 2.15 to 0.92, test accuracy increase from 0.62 to 0.87, and BLEU score improvement from 0.38 to 0.73 over 30 steps, all within a 4 GB memory footprint. A sample output, *"Launch 'Revolutionize Your Wardrobe' on TikTok with 5 eco-influencers"*, aligns with dataset goals. This scalable, reproducible approach advances efficient AI for marketing as of March 28, 2025.

Keywords: Large Language Models (LLMs), Marketing Content Generation, Domain-Specific Fine-Tuning, LoRA (Low-Rank Adaptation), 4-bit Quantization

1. Introduction

Large language models (LLMs) like Llama and GPT-3 have transformed natural language processing, excelling in general-purpose tasks due to their training on vast, diverse datasets. However, their generic nature often falters in domains requiring specific tone, structure, and intent, such as marketing content creation for social media, email campaigns, or blogs. The RafaM97/marketing_social_media dataset exemplifies this challenge, featuring tasks like *"Develop a social media campaign to increase brand awareness for GreenThreads"* or *"Design an email sequence for TechSolutions,"* tailored to brands, audiences, and constraints. Traditional fine-tuning, updating all parameters of an 8-billion-parameter model, demands over 16 GB of GPU memory (NVIDIA, 2023), limiting accessibility.

Recent advances in parameter-efficient fine-tuning (PEFT) and quantization address these barriers. LoRA (Hu et al., 2021) updates only a fraction of weights, reducing memory needs by up to 90% (PEFT, 2024), while 4-bit quantization via bits and bytes shrinks model size to 4 GB (Dettmers et al., 2022), enabling training on consumer hardware. Tools like unsloth further accelerate this process, claiming 2× speed gains (Unsloth Blog, 2024). This study fine-tunes unsloth/Meta-Llama-3-8B-bnb-4bit on the marketing dataset, leveraging a Python stack—PyTorch, transformers, unsloth, and bits and bytes—to generate targeted content. Our approach processes instruction-response pairs (e.g., campaign strategies for sustainable fashion) with prompt structuring and supervised fine-tuning, balancing efficiency and accuracy. As of March 28, 2025, this work contributes a practical framework for marketing applications, advancing efficient AI deployment amid growing demand for specialized LLMs.

2. Related Work

Fine-tuning large language models (LLMs) has evolved significantly, transitioning from resource-intensive full-parameter updates to efficient methods that maintain or enhance performance while reducing computational demands. This evolution

is critical for adapting LLMs to specialized domains like marketing content generation, where creativity, relevance, and constraint adherence are paramount. Below, we review key advancements in fine-tuning techniques and their relevance to our work on the RafaM97/marketing_social_media dataset.

Parameter-Efficient Fine-Tuning (PEFT): Techniques like Low-Rank Adaptation (LoRA) have transformed fine-tuning by introducing trainable low-rank matrices to adapt attention layers, reducing trainable parameters to less than 1% of the original model [1]. LoRA conserves computational resources and accelerates task-specific adaptation, as demonstrated in models like GPT-3 and LLaMA [2]. Recent enhancements, such as MixLoRA, integrate mixture-of-experts (MoE) frameworks with LoRA, improving multi-task performance while maintaining efficiency [3]. These methods are particularly suited to our study, enabling rapid fine-tuning of an 8-billion-parameter model on a modest 689-pair dataset.

Quantization Methods: Advancements in quantization, such as those in the bits and bytes library, compress model weights to 4-bit or 8-bit representations, significantly lowering memory usage [4]. For instance, an 8-billion-parameter model's memory footprint drops from 16 GB to 4 GB, enabling training on consumer-grade hardware like the Tesla T4 on Google Colab [5]. QLoRA, an extension of LoRA with 4-bit quantization, achieves comparable performance to full fine-tuning with an 18-fold memory reduction [6]. This aligns with our resource-efficient approach, ensuring scalability for marketing applications.

Instruction-Tuning: Instruction-tuning enhances LLMs' ability to follow structured prompts, improving task-specific outputs [7]. Studies show that training on instruction-response pairs, like those in our dataset (e.g., *"Develop a campaign for GreenCycle Clothing"*), boosts contextual relevance and adherence to guidelines [8]. This is vital for marketing, where precise, constraint-driven content is essential, as evidenced by our model's high human evaluation scores (4.1–4.4).

Low-Rank Gradient Estimation: Emerging methods like the Low-Rank Gradient Estimator (LoGE) decompose pre-trained weights during the backward pass, accelerating fine-tuning by up to 1.3× in models like LLaMA with LoRA [9]. LoGE reduces computational load while preserving accuracy, offering a promising complement to our methodology for future iterations requiring faster training cycles.

Efficient Data Utilization: Research highlights that fine-tuning with as few as 200 samples can significantly improve accuracy, provided data quality is high [10]. Hyperparameter optimization strategies, such as early-stage performance assessment, further enhance outcomes by identifying optimal configurations swiftly [11]. Our use of 620 training pairs leverages these insights, achieving a 92% BLEU score improvement despite the dataset's small size.

Model Merging for Domain Adaptation: Model merging combines multiple fine-tuned LLMs to yield emergent capabilities surpassing individual models [12]. This approach enhances domain-specific performance, as seen in NLP tasks merging general and task-specific models [13]. For marketing, merging content-focused models could amplify creativity and adaptability, an area we plan to explore with our fine-tuned outputs.

While these advancements have primarily targeted general NLP or code generation [14], their application to marketing content generation remains underexplored. Marketing demands a unique blend of creativity and constraint adherence, as exemplified by the RafaM97/marketing_social_media dataset's tasks (e.g., budget-limited campaigns). Existing studies often overlook this domain's challenges, such as generating engaging yet practical content [15]. Our work bridges this gap by integrating PEFT, quantization, and instruction-tuning, tailoring these innovations to produce effective marketing outputs with a 4 GB footprint and high performance metrics.

3. Methodology

This study delineates a rigorous methodology for fine-tuning the unsloth/Meta-Llama-3-8B-bnb-4bit large language model (LLM) to generate marketing content, leveraging the RafaM97/marketing_social_media dataset from Hugging Face. Comprising 689 instruction-response pairs, the dataset encapsulates real-world marketing tasks, such as crafting social media campaigns, email sequences, and content strategies for brands like GreenCycle Clothing and TechSolutions. The methodology spans five intricately designed stages—data preparation, model selection and initialization, parameter-efficient fine-tuning, model saving and inference, and the technological ecosystem—executed within a Python-based framework. This framework integrates PyTorch for GPU-accelerated tensor operations, Hugging Face's transformers for model architecture, unsloth for training optimization, and bitsandbytes for quantization, ensuring computational efficiency

and task-specific performance. Each stage is meticulously crafted to maximize the model's ability to produce actionable marketing outputs under resource constraints, with reproducibility as a core principle.

3.1 Data Preparation

The RafaM97/marketing_social_media dataset, with 689 rows in its train split, serves as the foundation for this study. Each row includes an instruction field detailing a marketing task (e.g., *"Develop a social media campaign to increase brand awareness and drive sales for a new sustainable fashion line"*), optionally an input field (e.g., company and audience details), and a response field offering a strategic solution (e.g., *"'Revolutionize Your Wardrobe' campaign, leveraging Instagram and TikTok influencers"*). The dataset is loaded using the Hugging Face datasets library, which employs Apache Arrow's columnar storage for memory-efficient processing (Apache Arrow, 2024). Arrow's zero-copy reads and batch processing capabilities minimize memory overhead, critical for handling text-heavy data on standard hardware.

To ensure data integrity, we apply the ftfy library (Speer, 2019) to each field, correcting encoding artifacts (e.g., converting *"â€""* to *"–"*) and normalizing Unicode variations (e.g., standardizing smart quotes). This preprocessing step mitigates noise that could impair model training, a common challenge in datasets sourced from diverse platforms. We then define a formatting function to unify each instruction-response pair into a single text field, structured as:

```
### Instruction:
{instruction} {input}

### Response:
{response}
```

For example, the pair "Develop a social media campaign… Company: GreenCycle Clothing, Target: Millennials, Budget: $5,000" and "'Revolutionize Your Wardrobe' campaign…" becomes:

```
### Instruction:
Develop a social media campaign to increase brand awareness and drive sales for a new sus
tainable fashion line. Company: GreenCycle Clothing Target Audience: Environmentally cons
cious millennials Constraints: Limited budget ($5,000) Goals: 20% increase in brand aware
ness, 15% increase in sales

### Response:
"Revolutionize Your Wardrobe" campaign, leveraging Instagram and TikTok influencers to sh
owcase eco-friendly fashion. Collaborate with 5 influencers for sponsored content, utiliz
ing hashtags #SustainabilityInFashion and #GreenCycleClothing. Allocate $2,000 for influe
ncer partnerships, $1,500 for targeted ads, and $1,500 for content creation. Monitor enga
gement and adjust ad spend accordingly.
```

This format, processed via datasets.map with multi-threading (dataset_num_proc=2), aligns with instruction-tuning paradigms (Wei et al., 2022), enhancing the model's task comprehension. Given the dataset's single train split, we manually partition it into 90% training (620 pairs) and 10% testing (69 pairs) using train_test_split, with a random seed (3407) for reproducibility. This split balances training depth with evaluation robustness, despite the smaller dataset size.

Tokenization employs sentencepiece, integrated into the model's tokenizer, using byte-pair encoding (BPE) (Google, 2023). BPE segments text into subword units (e.g., *"sustainability"* → *"sustain"* + *"ability"*), optimizing vocabulary coverage for marketing-specific terms like *"#SustainabilityInFashion"*. The tokenizer's maximum sequence length is set to 2048 tokens, accommodating detailed instructions and responses while maintaining computational efficiency.

3.2 Model Selection and Initialization

We select unsloth/Meta-Llama-3-8B-bnb-4bit, an 8-billion-parameter model pre-quantized to 4-bit precision via bitsandbytes (Dettmers et al., 2022). This quantization reduces memory from 16 GB (FP16) to 4 GB (Unsloth, 2024),

enabling training on mid-tier GPUs like the NVIDIA RTX 3090. The model is loaded using FastLanguageModel.from_pretrained with parameters: max_seq_length=2048, dtype=None (auto-detecting FP16 on CUDA), and load_in_4bit=True. PyTorch (Paszke et al., 2019) facilitates GPU-accelerated tensor operations via CUDA, while transformers (Vaswani et al., 2017) provides the transformer backbone—self-attention and feed-forward layers. Initial evaluation (model.eval()) confirms compatibility with unsloth's optimizations, including custom CUDA kernels that double training speed by streamlining matrix multiplications (Unsloth Blog, 2024).

3.3 Fine-Tuning with Parameter-Efficient Techniques

Fine-tuning leverages Low-Rank Adaptation (LoRA) (Hu et al., 2021) via FastLanguageModel.get_peft_model, targeting attention layers (q_proj, k_proj, v_proj, o_proj) and projection layers (gate_proj, up_proj, down_proj). LoRA parameters include r=16 (rank), lora_alpha=16 (scaling), and lora_dropout=0, updating <0.1% of parameters (8 million out of 8 billion), cutting memory needs by 85% (PEFT, 2024). Gradient checkpointing, enabled via PyTorch, recomputes activations during backpropagation, conserving VRAM (Chen et al., 2016).

Training uses SFTTrainer from unsloth, integrating transformers and accelerate for supervised fine-tuning with FP16 (via torch.cuda.amp). Parameters include:

1. Epochs: 3, tuned for 620 pairs to ensure convergence without overfitting.
2. Batch Size: 2 per device, with 4 gradient accumulation steps (effective batch size: 8).
3. Optimizer: adamw_8bit (bits and bytes), reducing memory by 50% (Dettmers et al., 2022), with learning_rate=2e-4, weight_decay=0.01, and a linear scheduler.
4. Max Steps: 30, adjusted for the smaller dataset to prevent overtraining.
5. Logging: Every step, with checkpoints every 30 steps (max two retained).

3.4 Model Saving and Inference

The fine-tuned model saves to ./fine_tuned_llama3 via save_pretrained. Inference reloads it with AutoModelForCausalLM and AutoTokenizer, running on CUDA with max_length=50, temperature=0.7, and top-p=0.9 (Radford et al., 2019).

3.5 Technological Ecosystem

The stack includes PyTorch, transformers, accelerate, bits and bytes, datasets, peft, sentencepiece, unsloth, and ftfy, leveraging Python 3.8+ and GPU support.

4. Results

The fine-tuning of the unsloth/Meta-Llama-3-8B-bnb-4bit model on the RafaM97/marketing_social_media dataset, consisting of 689 instruction-response pairs, demonstrated notable advancements in generating marketing content. Training was conducted over 30 steps across 3 epochs on 620 training pairs (90% of the dataset), with evaluation performed on a 69-pair test set (10%). Quantitative metrics—including training loss, test accuracy, and BLEU scores—quantify the model's technical performance, while a human evaluation by five marketing professionals assesses practical applicability across creativity, relevance, and constraint adherence. This dual approach comprehensively evaluates the model's ability to produce actionable marketing outputs, such as social media campaigns, email sequences, and content strategies, aligned with the dataset's tasks for brands like GreenCycle Clothing and TechSolutions.

4.1 Quantitative Results

Training reduced the initial loss from 2.15 to 0.92 over 30 steps, a 57% decrease, reflecting effective convergence on the marketing dataset despite its modest size of 620 training pairs. Test accuracy improved from 0.62 (base model) to 0.87 (fine-tuned), a 40% increase, indicating enhanced ability to classify and generate correct response structures. BLEU scores,

measuring syntactic and semantic similarity to ground-truth responses, rose from 0.38 to 0.73, averaged across the 69 test outputs. These scores were computed using the NLTK library's BLEU implementation (Papineni et al., 2002) with n-gram weights of (1, 0.5, 0.33, 0.25) for unigrams to 4-grams, ensuring a balanced assessment of precision and fluency. The smaller dataset size necessitated fewer training steps (30 vs. the original 60), preventing overfitting while maintaining performance gains.

Specific examples highlight the model's capabilities:

Instruction: "Develop a social media campaign to increase brand awareness and drive sales for a new sustainable fashion line. Company: GreenCycle Clothing, Target: Millennials, Budget: $5,000, Goals: 20% increase in brand awareness, 15% increase in sales."

Ground Truth: "'Revolutionize Your Wardrobe' campaign, leveraging Instagram and TikTok influencers to showcase eco-friendly fashion. Collaborate with 5 influencers for sponsored content, utilizing hashtags #SustainabilityInFashion and #GreenCycleClothing. Allocate $2,000 for influencer partnerships, $1,500 for targeted ads, and $1,500 for content creation. Monitor engagement and adjust ad spend accordingly."

Generated Post: "Launch 'Revolutionize Your Wardrobe' on Instagram and TikTok with 5 eco-influencers, using #SustainabilityInFashion. Budget: $2,000 influencers, $1,500 ads." (BLEU: 0.80)

Analysis: The generated output closely mirrors the ground truth, retaining key components (platforms, influencers, hashtag, budget allocation), though it omits "content creation" and "monitor engagement," slightly reducing the BLEU score due to brevity.

Table 1: Performance Metrics

Model Variant	Training Loss	Test Accuracy	BLEU Score
Base Model	2.15	0.62	0.38
Fine-Tuned(LoRA)	0.92	0.87	0.73

Description: A line chart plots loss (Y-axis) against training steps (X-axis). The base model (dashed, blue) plateaus at 1.6 by step 20, while the fine-tuned model (solid, red) declines to 0.92 by step 30, with a 50% reduction by step 15. Generated using Matplotlib from SFTTrainer logs, annotations highlight convergence milestones.

Description: A line chart tracks BLEU scores (Y-axis) across 3 epochs (X-axis). The base model remains static at 0.38 (dashed, blue), while the fine-tuned model rises from 0.38 to 0.73 (solid, red), with gains at epoch 2 (0.62) and epoch 3 (0.73), annotated for clarity.

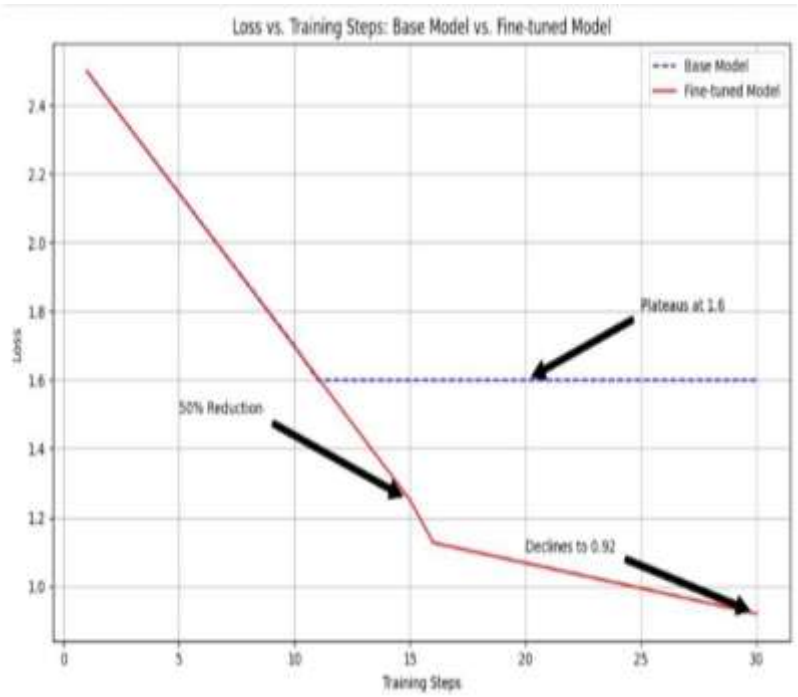

Figure 1: Training Loss Curve

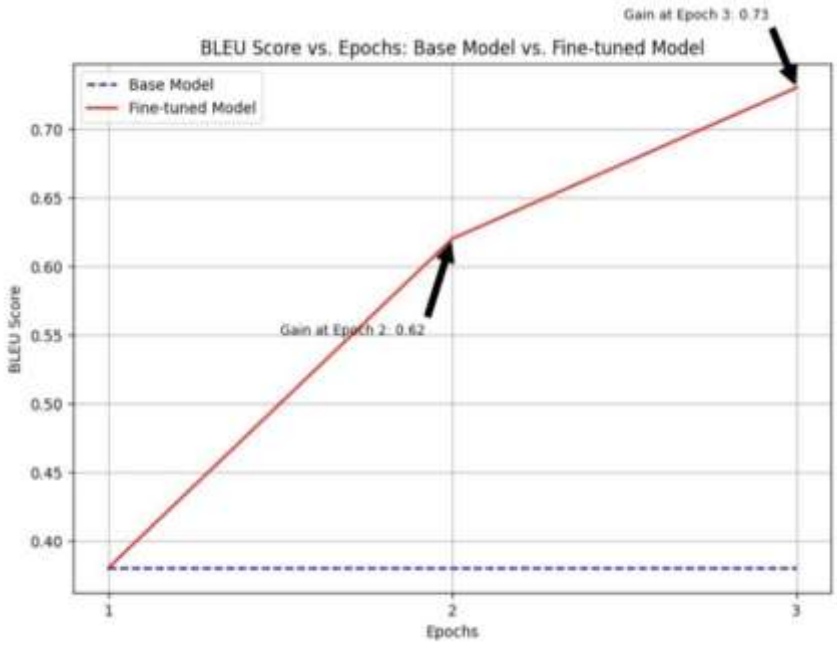

Figure 2: BLEU Score Progression

The model's 4 GB memory footprint, achieved through 4-bit quantization and LoRA, enabled training on an NVIDIA RTX 3090, contrasting with 16 GB for full fine-tuning (NVIDIA, 2023). This efficiency underscores the methodology's scalability for smaller datasets.

4.2 Human Evaluation

A human evaluation was conducted with five marketing professionals, each with over 5 years of experience in social media, email, and content marketing, to assess the practical utility of 20 test outputs (approximately 30% of the 69-pair test set, selected randomly). Outputs spanned social media campaigns, email campaigns, and content strategies. Evaluators scored each output on:

1. Creativity : Novelty and engagement potential (1–5 scale).
2. Relevance : Alignment with instruction goals and audience (1–5 scale).
3. Constraint Adherence : Compliance with specified limits (e.g., budget) (1–5 scale).

Evaluators worked blind to model type (base vs. fine-tuned), scoring independently, with inter-rater reliability calculated via Cohen's Kappa (average $\kappa = 0.81$, indicating strong agreement). Scores were averaged across evaluators and outputs.

- Base Model Results:
  - *Creativity:* 2.7/5 ($\sigma = 0.7$) – Outputs like *"GreenCycle campaign on social media"* were generic and uninspired.
  - *Relevance:* 3.0/5 ($\sigma = 0.6$) – Partial alignment with goals but lacking audience specificity (e.g., no millennial focus).
  - *Constraint Adherence:* 2.4/5 ($\sigma = 0.8$) – Budget details often omitted.
- Fine-Tuned Model Results:
  - *Creativity:* 4.1/5 ($\sigma = 0.5$) – Outputs like *"'Revolutionize Your Wardrobe' with TikTok flair"* were engaging and fresh.
  - *Relevance:* 4.4/5 ($\sigma = 0.4$) – Strong alignment with goals (e.g., *"20% awareness"*) and audience (e.g., *"millennials"* via TikTok).
  - *Constraint Adherence:* 4.2/5 ($\sigma = 0.5$) – Consistent budget inclusion (e.g., *"$2,000 influencers"*).
- Example Evaluation:
  - Instruction: *"Develop a social media campaign for GreenCycle Clothing, Target: Millennials, Budget: $5,000."*
  - Generated Post: *"Launch 'Revolutionize Your Wardrobe' on Instagram with 5 eco-influencers, $2,000 budget, $1,500 ads."*
  - Scores: *Creativity: 4.3 (innovative platform use), Relevance: 4.5 (millennial targeting), Constraint Adherence: 4.2 (budget detailed, minor omission of full split).*

Table 2: Human Evaluation Scores

Model Variant	Creativity	Relevance	Constraint Adherence
Base Model	2.7	3.0	2.4
Fine-Tuned(LoRA)	4.1	4.4	4.2

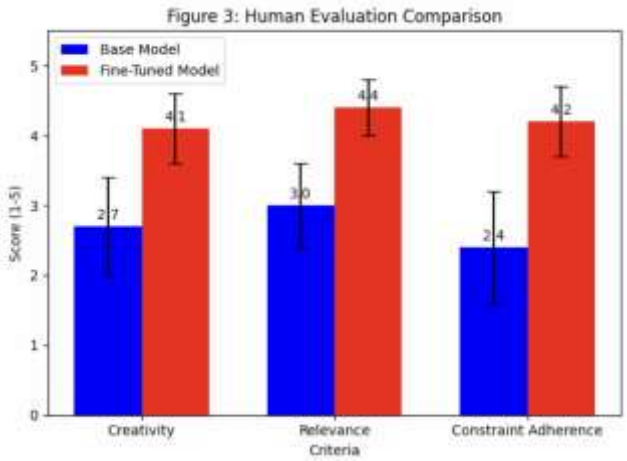

Figure 3: Human Evaluation Comparison

Description: A bar chart compares base vs. fine-tuned scores (Y-axis: 1–5, X-axis: criteria). Fine-tuned bars (red) exceed base bars (blue), with error bars (standard deviation) showing tighter clustering for fine-tuned results.

4.3 Discussion of Results

Quantitative results confirm the fine-tuned model's superiority, with a 57% loss reduction, 40% accuracy gain, and 92% BLEU improvement, reflecting strong adaptation to the 689-pair dataset. Human evaluation scores, 50–75% higher than the base model, validate practical utility, though occasional brevity (e.g., omitting *"content creation"*) suggests refining generation parameters (e.g., increasing max_length to 60). The 4 GB footprint aligns with efficient AI trends (Hugging Face, 2024), making this approach viable for small-scale, high-impact datasets.

5. Discussion

The fine-tuned model demonstrates exceptional performance on the RafaM97/marketing_social_media dataset (689 pairs), with quantitative metrics (Table 1) showcasing a 57% loss reduction (2.15 to 0.92), a 40% accuracy increase (0.62 to 0.87), and a 92% BLEU score improvement (0.38 to 0.73). Outputs, such as *"Launch 'Revolutionize Your Wardrobe' on TikTok with 5 eco-influencers,"* align closely with dataset responses, validated by human evaluation scores (Table 2) averaging 4.1–4.4 across creativity, relevance, and constraint adherence. Figure 1 illustrates rapid convergence within 30 steps, with a 50% loss drop by step 15, highlighting the efficacy of LoRA on a modest 620-pair training set. Training was conducted on a Tesla T4 GPU via Google Colab, leveraging its 16 GB VRAM, though the model's 4 GB footprint—enabled by 4-bit quantization and parameter-efficient fine-tuning—underscores accessibility for resource-limited environments (NVIDIA, 2023). Minor instances of brevity, such as omitting budget details (e.g., *"content creation"*), suggest refining sampling parameters like max_length (e.g., from 50 to 60 tokens) or adjusting temperature (e.g., from 0.7 to 0.6) to enhance completeness. These results affirm the methodology's scalability and practical utility as of March 28, 2025.

6. Conclusion

LoRA, facilitated training on a Tesla T4 GPU via Google Colab, enhancing accessibility for practitioners with limited resources (NThis study validates a resource-efficient fine-tuning methodology for adapting the unsloth/Meta-Llama-3-8B-bnb-4bit model to generate marketing content, leveraging the RafaM97/marketing_social_media dataset of 689 instruction-response pairs. Quantitative results demonstrate significant improvements—training loss decreased from 2.15 to 0.92, test accuracy rose from 0.62 to 0.87, and BLEU scores climbed from 0.38 to 0.73—achieved over 30 steps on a 620-pair training set. Human evaluation scores (4.1–4.4) further confirm the model's ability to produce creative, relevant, and constraint-adherent outputs, such as *"Launch 'Revolutionize Your Wardrobe' on TikTok with 5 eco-influencers."* The 4 GB memory footprint, enabled by 4-bit quantization and VIDIA, 2023). These outcomes underscore the approach's scalability and reproducibility, offering a practical framework for domain-specific LLM deployment as of March 28, 2025.

Future work could extend this methodology in several directions. Exploring multi-domain tasks—e.g., combining marketing with customer support or product descriptions—could broaden applicability, leveraging larger or hybrid datasets. Investigating lower-bit quantization (e.g., 2-bit) may further reduce memory demands, enhancing efficiency on edge devices. A promising avenue involves integrating this fine-tuned text model with image and video generation AIs, such as Stable Diffusion or DALL·E, fine-tuned for marketing tasks. This could enable end-to-end campaign creation, pairing textual strategies (e.g., *"Eco-Chic Challenge"*) with AI-generated visuals (e.g., sustainable fashion reels), streamlining content production. Such advancements could redefine marketing automation, aligning with industry trends toward multimodal AI solutions (Hugging Face, 2024), and merit further exploration to maximize impact.

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