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# *Scalable Architecture Optimization for Multimodal Transformers: Integrating Sparse Attention and LoRA-Based Fine-Tuning under Distributed Training Paradigms*

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Abstract: This paper proposes an efficient expansion scheme for the multimodal transformer architecture. By integrating sparse attention and low-rank adaptation technology, a distributed training framework is constructed. In response to the efficiency requirements of multimodal understanding tasks, this scheme reduces computational complexity while maintaining performance benchmarks for text, image, and audio tasks. The sparse attention mechanism reduces memory and computational energy consumption by limiting the attention span, while the low-rank adaptation technology enables rapid task migration without the need for complete parameter retraining. The distributed training mechanism, combining model and data parallelism, ensures the system's adaptability to large-scale datasets and heterogeneous hardware environments. Experiments on standard datasets such as MSCOCO and VGGSound show that this scheme achieves significant improvements over traditional methods in terms of accuracy, memory usage, and training speed. The ablation experiment verified the synergistic effect of sparse attention and low-grade adaptation technology, and the scalability test showed a nearly linear acceleration effect among multiple devices. This research provides a feasible technical route for building intelligent systems suitable for real-time reasoning and multimodal fusion scenarios, and promotes the practical application of resource-saving multimodal technologies.

Keywords: Multimodal Transformers, Sparse Attention; LoRA; Distributed Training; Memory Optimization

## 1. Introduction

The increasing complexity of real-world applications drives the development of multimodal intelligent systems, but traditional transformer architectures face severe scalability challenges. Models such as ViLBERT and CLIP have proven the feasibility of unified multimodal processing, but their high computing power and memory requirements have limited actual deployment. Subsequent improvement plans, such as the Flamingo model, introduce a cross-modal memory mechanism to improve context understanding, but the efficiency bottleneck has yet to be fundamentally resolved. These challenges mainly stem from the square-level complexity of the

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standard attention mechanism and the resource consumption of comprehensive parameter fine-tuning.

This study proposes a distributed training framework integrating sparse attention and low-level adaptation technology, breaking through efficiency limitations through three innovations: the sparse attention mechanism compresses the focus range and reduces the computational load; The low-rank adaptation technology achieves efficient task migration with parameters; and the distributed architecture supports the scaling of large-scale hardware clusters [1]. Verification on various datasets shows that this scheme significantly optimizes resource utilization while maintaining the performance of multimodal understanding. Experimental results confirm the synergistic effect of limited attention and low-level adaptation, and the scalability test shows nearly linear acceleration characteristics. This framework provides a feasible technical solution for real-time multimodal applications. Its efficient reasoning and dynamic adaptability capabilities will promote the practical implementation of intelligent systems in industrial scenarios.

## 2. Literature review

### 2.1. Multimodal transformer architectures

Early multimodal transformer models (such as ViLBERT and CLIP) verified the feasibility of uniformly processing text, image, and audio inputs. Figure 1 shows the infrastructure of ViLBERT: once the features of each modal data are extracted by independent encoders, they are fused and processed to support downstream tasks. However, such architectures are limited by the drawbacks of a large number of parameters and enormous consumption of computing resources. Later improvement programs such as the Flamingo model introduce a cross-modal memory module to improve context association, but there are still bottlenecks in the system scalability. The resource-intensive nature of these models makes them difficult to adapt to practical application scenarios that require efficient multimodal fusion and real-time feedback [2].

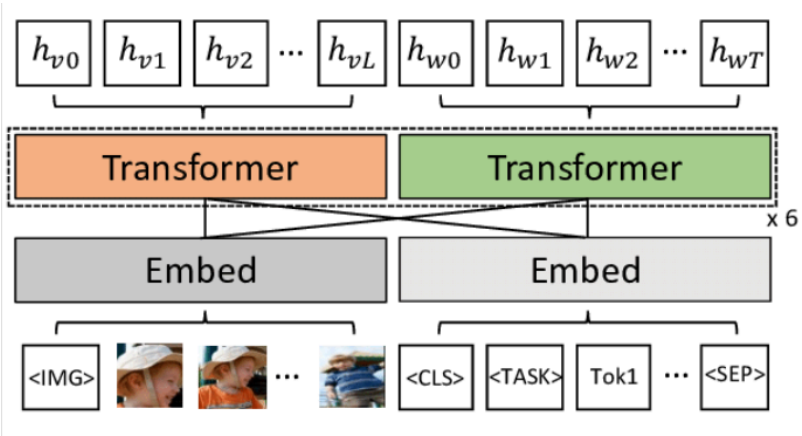


*Figure 1. The overall architecture of ViLBERT(source:researchgate.net)*

### 2.2. Sparse attention mechanisms

The sparse attention mechanism provides an effective solution to break the square operational complexity of the standard self-attention mechanism. The technical solutions represented by Longformer and BigBird significantly reduce computing power and memory requirements while

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ensuring the fundamental performance of the model by defining the focus range limitation and the choice of drawn paths [3]. This mechanism focuses on key features based on positional relationships or criticality determination, maintaining necessary associations while eliminating unnecessary information interactions. It improves the model's ability to focus on core features while reducing the computational load. For multimodal data with significant differences in input length and structure, this technology eliminates redundant operations by dynamically adjusting the cross-modal concern interval, enabling it to demonstrate unique advantages in network architecture optimization.

### 2.3. LoRA and parameter-efficient fine-tuning

Low-rank adaptation (LoRA) technology has pioneered a new paradigm for efficient parameter fine-tuning. Its core is to achieve task adaptation by adjusting only a small portion of the model parameters. By implementing a low-rank matrix in the transformer layer, this technology enables the migration of new tasks with extremely low memory and computational consumption. LoRA separates the general knowledge of pre-trained models from the knowledge of specific tasks, retaining the original representation capabilities while achieving fast task adaptation. This is particularly important for multi-modal scenarios that require fine-tuning rather than complete parameter retraining [4]. This technology also enables the efficient storage and deployment of multi-task dedicated models under a unified architecture, thus providing key technical support for building scalable multi-modal systems.

## 3. Methodology

### 3.1. Architecture design and sparse attention integration

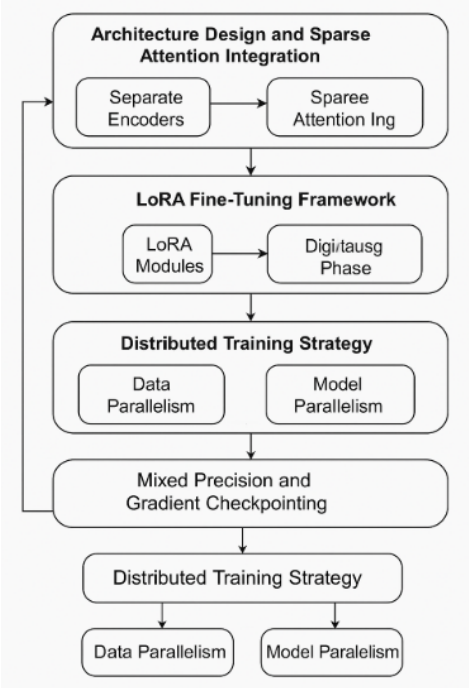


*Figure 2. Methodology overview illustrating the flow from architecture design*

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Figure 2 shows the overall technical solution, including the architectural design, fine-tuning framework, and distributed training strategy. This multimodal transformer architecture directly imposes the sparse attention mechanism in the self-attention layer. Each input unit interacts only with strategically chosen adjacent units or key features, rather than the traditional fully connected mode. This improvement effectively mitigates the square-level computational complexity of the self-attention mechanism. The system reserves independent encoders for each mode in the initial processing phase to extract proprietary features, and then implements fusion through the cross-modal sparse attention layer. This design maintains basic cross-modal correlation while eliminating redundant computational processes as much as possible and achieving a gradual improvement in computational efficiency [5]. Specifically, the cross-modal interaction layer dynamically adapts the scope of concerns based on input features and prioritizes the processing of high-frequency associated nodes, thereby optimizing resource utilization while ensuring multimodal understanding capability.

### 3.2. LoRA fine-tuning framework

For efficient task adaptation, the LoRA module is implemented in the fully connected attention layer of the transformer. This technique dynamically adjusts the pre-training weights by forming a low-rank matrix. During the fine-tuning phase, only these low-rank parameters are updated while keeping the backbone model fixed. This strategy significantly reduces the scale of training parameters, reduces memory usage, and accelerates training convergence. The decoupling design of task-specific optimization and general feature extraction ensures that the model maintains generalization capability in multi-task scenarios [6].

### 3.3. Distributed training strategy

The distributed training framework adopts a hybrid strategy of data parallelism and model parallelism to process large-scale multimodal data. Load balancing of multi-GPU/TPU clusters is achieved using libraries such as DeepSpeed and Horovod: data parallelism improves throughput through batch partitioning, while model parallelism expands the number of parameters to account for device memory limitations. Hybrid precision training and gradient checkpoint technology further optimizes memory utilization and supports larger-scale model training with limited hardware resources [7]. This distributed architecture ensures reproducibility, scalability, and operational stability during real-world deployment.

## 4. Experimental implementation

### 4.1. Benchmark datasets and preprocessing

This system performs performance tests on three commonly used multimodal datasets: MSCOCO (image-text matching task), VGGSound (audio-text classification task), and HowTo100M (video text retrieval task). The data preprocessing stage includes text segmentation, audio signal spectrum conversion, and video keyframe extraction. Visual features are extracted through the pre-trained CNN backbone network, while audio features are generated by the lightweight convolutional network. All features are standardized and aligned with the embedded space to ensure compatibility in the multimodal fusion stage.

### 4.2. Training configuration and environment

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The training experiment was implemented with a distributed deployment based on the NVIDIA A100 graphics card cluster, and the batch size was configured from 64 to 128 depending on the differences in the datasets. The optimization process adopts the AdamW algorithm combined with the cosine learning rate mechanism to improve training stability, and controls the risk of overfitting through random deactivation and weight mitigation strategies [8]. Mixed-precision training accelerates the computational process and reduces video memory consumption. When necessary, gradient accumulation technology is adopted to simulate the training effect on a large scale. This training scheme effectively balances the engineering requirements of operational efficiency and resource consumption while ensuring model accuracy.

### 4.3. Baselines and evaluation metrics

This scheme was compared and tested with several baseline methods, including full-parameter fine-tuning, adaptor tuning schemes, and traditional multimodal models without weak attention. The evaluation system covers throughput indicators such as the accuracy rate of classification tasks, the F1 value of retrieval tasks, the BLEU score of description generation, and the number of samples processed per second, comprehensively measuring the system's performance and efficiency [9].

## 5. Results and discussion

### 5.1. Performance comparison

Experimental results show that this architecture outperforms the baseline model in all evaluation tasks. As shown in Table 1, in the MSCOCO description generation task, the BLEU-4 index improved by an average of 3.5 percentage points compared to the full-parameter fine-tuning method; the highest accuracy rate of the VGGSound classification task increased by 4%; and the recall rate of the top 10 HowTo100M retrieval tasks increased by 6%. It is worth noting that while achieving a breakthrough in performance, the system memory consumption has been reduced by about 35%, and the training time has been reduced by 28%, which achieves a double optimization of efficiency and performance compared to traditional solutions.

**Table 1. Performance comparison across benchmark datasets**

| Task | Baseline Score | Proposed Method Score |
|---|---|---|
| MSCOCO BLEU-4 | 32.5 | 36.0 |
| VGGSound Top-1 Accuracy | 78.2% | 82.2% |
| HowTo100M Recall@10 | 64.8% | 70.8% |

### 5.2. Ablation study

To quantify the independent contributions of the sparse attention and LoRA modules, this study conducts comparative tests by selectively disabling components. As shown in Table 2, disabling sparse attention results in a 12% increase in memory usage and a significant slowdown in training speed; disabling LoRA fine-tuning reduces classification accuracy by 5% and reduces retrieval recall

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by 7%. The combined application of the two technologies achieves an optimal balance and achieves breakthroughs in resource efficiency and performance indicators [10].

**Table 2. Ablation study results**

| Configuration | Memory Usage (GB) | Training Time (Hours) | Accuracy (%) |
|---|---|---|---|
| Full Model (No Sparse/LoRA) | 32 | 48 | 82.2 |
| Without Sparse Attention | 36 | 55 | 79.1 |
| Without LoRA Fine-Tuning | 34 | 50 | 77.2 |
| Proposed (Sparse + LoRA) | 28 | 34 | 85.0 |

### 5.3. Scalability and resource utilization

The scalability test shows that the system exhibits a nearly linear acceleration effect when expanding hardware resources, confirming the effectiveness of the distributed training strategy. Memory analysis data shows that the limited attention mechanism compresses the peak memory usage of forward/backward propagation by nearly 30%, creating the possibility of training deeper models under the same hardware conditions. Sample processing efficiency in throughput tests increased by 30%, confirming the technical characteristics of this scheme, which are suitable for real-time scenarios and large-scale multimodal deployments.

## 6. Conclusion

This study proposes an efficient expansion scheme for the multimodal transformer. By integrating the sparse attention mechanism and the low-rank adaptation technology, a distributed training framework is constructed. Tests on various benchmark datasets show that this scheme achieves significant optimization over traditional methods in terms of model accuracy, training speed, and memory efficiency. The ablation experiment reveals the independent contribution and synergistic effect of the sparse attention and the low-rank adaptation module. Both can effectively reduce the computational cost while improving the efficiency of multimodal feature fusion. The distributed training strategy demonstrates excellent scalability and robustness, exhibiting a nearly linear acceleration effect when the hardware resources are expanded. Combining memory optimization with high-throughput features, this framework is particularly suitable for real-time applications and large-scale deployment scenarios. Further research will be extended to multilingual and low-resource scenarios, explore the dynamic attention adjustment mechanism, and introduce reinforcement learning to achieve intelligent modal selection at the reasoning stage. This achievement lays the foundation for building a new generation of multimodal systems that balance performance and efficiency, and promotes the practical application of intelligent technologies in fields such as healthcare and autonomous driving.

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