Topic

GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints

Authors of orignal work
Joshua Ainslie∗ , James Lee-Thorp∗ , Michiel de Jong∗††
Yury Zemlyanskiy, Federico Lebrón, Sumit Sanghai

Noman Tahir

For code and results
github.com/nomangureshi1/NlPresearch

AI Assistance and Usage

Generative AI tools were used to enhance grammar, clarity, and readability while ensuring the originality of our research. Additionally, AI-assisted debugging helped optimize code, fix errors, and improve execution efficiency without altering the experimental design. The core analysis, methodology, and findings remain entirely our own.

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1 Introduction

1.1 Overview of the Topic

Transformer models have transformed NLP, but Multi-Head Attention (MHA) is computationally expensive. Multi-Query Attention (MQA) improves efficiency by sharing key-value pairs, trading accuracy for speed. This study optimizes MHA into MQA, excluding Grouped-Query Attention (GQA), to focus on efficiency.

1.1 Objectives of the Assignment

This study aims to explore improvements in Transformer inference efficiency by analyzing Multi-Query Attention (MQA) in comparison to traditional Multi-Head Attention (MHA). While the original paper also examined Grouped-Query Attention (GQA), we primarily focus on MQA due to its efficiency benefits.

Our research extends the original work by emphasizing model efficiency, generalization within summarization tasks, and computational resource optimization.

The key objectives of this study are as follows:

1.1.1 Performance Evaluation in Summarization Tasks

Objective: Evaluate MQA models against MHA across multiple summarization datasets to assess their trade-offs between speed and accuracy.

Goals:

- Assess speed, accuracy, memory efficiency, and computational cost trade-offs between MHA and MQA.
- Compare model efficiency in real-world summarization applications.
- Investigate whether smaller, optimized models can achieve similar performance as large-scale architectures.

1.1.2 Model Efficiency s Scalability

Objective: Investigate whether MQA significantly reduces inference time compared to MHA while maintaining competitive performance.

Goals:

- Compare MHA vs. MQA performance across different summarization datasets (CNN/DailyMail, arXiv, and PubMed).
- Measure inference speed improvements and evaluate the impact on ROUGE scores.
- Identify whether MQA is more practical for real-time applications.

1.1.3 Generalization Across Summarization Datasets

Objective: Evaluate whether MQA models generalize well across different summarization datasets and long-form documents.

Goals:

- Extend evaluation to scientific papers (arXiv, PubMed) and real-world news articles (CNN/DailyMail).
- Analyze how well MQA adapts to long-form documents and structured text.

- Identify cases where MQA may struggle or require modifications for specific domain adaptation.

1.1.4 Memory s Computational Resource Optimization

Objective: Investigate the impact of memory usage and inference efficiency in different deployment environments (e.g., consumer hardware vs. high-performance GPUs).
Goals:

- Measure GPU/CPU memory usage per inference (tested on Mac M2 Max with MPS backend).
- Identify trade-offs between latency and accuracy when using MQA instead of MHA.
- Assess whether MQA's efficiency benefits make it suitable for real-time summarization applications.

1.2 How Our Study Differs from the Original Paper

The following table highlights the key differences between our study and the original research on MHA vs. MQA:

Table No 1

Aspect	Original Paper	Our Study (New Additions)
Evaluation Scope	Focused on NLP tasks (Summarization, Translation, QA).	Focused only on Summarization (CNN/DailyMail, arXiv, PubMed).
Model Comparisons	Compared MHA, MQA, and GQA on multiple tasks.	Compared only MHA vs. MQA, excluding GQA for a more focused evaluation.
Training C Adaptation	Converted MHA to MQA/GQA with fine-tuning.	Evaluates MHA vs. MQA without additional fine-tuning.
Metrics Analyzed	Evaluated accuracy and speed.	Added inference time analysis on Mac M2 Max.
Deployment Considerations	Did not analyze real-world device constraints.	Tested inference time on consumer hardware (Mac M2 Max) instead of high-end GPUs.
Findings on Speed C Accuracy	MQA was found to be faster, but accuracy trade-offs were not deeply analyzed.	Our results confirm that MQA improves inference speed, especially on shorter documents, but suffers a noticeable drop in ROUGE scores compared to MHA

2 Literature Review

2.1 Summary of Relevant Literature

The development of efficient and scalable transformer models has been a central focus in natural language processing, driven by advancements in attention mechanisms, model compression, and checkpoint adaptation.

The foundational work of Vaswani et al. (2017) introduced the Transformer architecture with multi-head attention, enabling parallel processing of input sequences. However, subsequent studies, such as Voita et al. (2019), revealed redundancy in attention heads, prompting research into more efficient mechanisms like multi-query attention (MQA). Shazeer (2019) pioneered MQA in "Fast Transformer Decoding: One Write-Head is All You Need", demonstrating its computational efficiency by sharing key and value heads across queries. Recent work by Ainslie et al. (2023) further generalized MQA in "Multi-Query Attention is All You Need", highlighting its applicability to large-scale models. Parallel efforts in efficient transformer architectures, such as the linear-time self-attention proposed by Wang et al. (2020) in "Linformer" and the comprehensive survey by Tay et al. (2020) in "Efficient Transformers: A Survey", have explored techniques to reduce the quadratic complexity of attention. Additionally, checkpoint adaptation methods like LoRA (Hu et al., 2021) and AdapterHub (Pfeiffer et al., 2020) have enabled efficient fine-tuning of pre-trained models, while model compression techniques, including DistilBERT (Sanh et al., 2019) and BERT compression (Zafrir et al., 2019), have addressed the trade-offs between model size and performance. These advancements collectively provide the groundwork for training generalized multi-query transformer models from multi-head checkpoints, balancing efficiency, scalability, and generalization.

3. Methodology

This section describes the experimental approach and the methodology used to evaluate the efficiency of Multi-Query Attention (MQA) compared to Multi-Head Attention (MHA) across summarization datasets.

3.1 Experimental Approach

Our study follows a structured experimental evaluation where we compare MHA and MQA across different summarization datasets using the T5 model family. The key steps in our methodology are:

1. **Model Selection**
    - We use T5-Large as the baseline for Multi-Head Attention (MHA).
    - We use Google/T5-Large-LM-Adapt for Multi-Query Attention (MQA).
2. **Dataset Selection**
    - We evaluate the models on three summarization datasets to test their generalization:
        - CNN/DailyMail (news summarization)
        - arXiv (scientific article summarization)
        - PubMed (medical research summarization)
3. **Evaluation Metrics**
    - We measure inference speed (time taken to generate summaries).
    - We evaluate accuracy using ROUGE scores (ROUGE-1, ROUGE-2, and ROUGE-L).
    - We measure memory efficiency by monitoring GPU/CPU usage.

4. **Deployment Considerations**
    - Unlike the original paper, which used high-end GPUs, we run experiments on Mac M2 Max using MPS (Metal Performance Shaders) for optimized inference.

3.2 Data Collection s Processing

3.2.1 Dataset Sources

- CNN/DailyMail – A dataset containing news articles paired with human-written summaries.
- arXiv – A collection of scientific research papers with structured abstracts.
- PubMed – A biomedical dataset containing medical research papers with abstract summaries

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3.2.2 Data Preprocessing

We applied minimal preprocessing to ensure consistency across models:

- Tokenized text using the T5 tokenizer.
- Used a maximum token length of 512 for input and 150 for output summaries.
- Applied truncation and padding to handle varying document lengths.
- Used a streaming dataset loading approach to minimize memory overhead.

3.3 Model Evaluation Process

1. **Model Inference**
    - We feed the tokenized input articles into each model.
    - The model generates summarized outputs.
    - We record inference time for each model.
2. **Performance Comparison**
    - We compute ROUGE scores for MQA and MHA summaries.
    - We compare accuracy (ROUGE scores) and efficiency (inference time, memory usage).
3. **Hardware Setup**
    - The experiments were conducted on Mac M2 Max (32GB RAM, MPS backend).
    - We optimized model execution using float16 precision for faster inference.

3.4 Summary of Methodology

Table No 2

Step	Details
Models Used	T5-Large (MHA), Google/T5-Large-LM-Adapt (MQA)
Datasets Used	CNN/DailyMail, arXiv, PubMed
Evaluation Metrics	ROUGE-1, ROUGE-2, ROUGE-L, Inference Time

Inference Hardware	Mac M2 Max, MPS backend, Float16 Precision
Key Differences	Evaluates MHA vs. MQA, excludes GQA, tests efficiency on consumer hardware

This methodology allows us to directly compare the efficiency and accuracy trade-offs between MHA and MQA in summarization tasks while testing their real-world applicability on Mac M2 Max.

4. Results

This section presents the findings from our experiments comparing Multi-Query Attention (MQA) and Multi-Head Attention (MHA) across different summarization datasets. We analyze the inference time, accuracy (ROUGE scores), and efficiency trade-offs between the two attention mechanisms.

4.1 Presentation of Findings

Our study evaluates T5-Large (MHA) and Google/T5-Large-LM-Adapt (MQA) on three datasets:

- CNN/DailyMail – News summarization
- arXiv – Scientific article summarization
- PubMed – Biomedical research summarization

We measure:

1. **Inference Time** – Time taken to generate summaries.
2. **ROUGE Score** – A measure of summary quality (ROUGE-1, ROUGE-2, ROUGE-L).
3. **Computational Efficiency** – Memory and processing speed improvements.

The following table presents the results of our evaluation:

Table No 3

Model	Dataset	Inference Time (s)	ROUGE-1 Score
MHA	CNN/DailyMail	3.064	0.385965
MQA	CNN/DailyMail	1.845	0.196721
MHA	arXiv	1.945	0.181818
MQA	arXiv	2.104	0.138249
MHA	PubMed	1.854	0.110553
MQA	PubMed	2.009	0.107843

Key Findings:

- **Inference Time:** MQA is consistently faster than MHA on CNN/DailyMail (by ~40%) but shows a slight increase in time for arXiv and PubMed.
- **ROUGE Score**: MHA consistently outperforms MQA in accuracy, with higher ROUGE-1 scores across all datasets.

4.2 Analysis and Interpretation

4.2.1 Speed vs. Accuracy Trade-offs

- MQA significantly improves inference speed, particularly on shorter texts (CNN/DailyMail).
  - For longer texts (arXiv, PubMed), MQA does not show a major speed advantage over MHA, likely due to the structured nature of scientific documents.
  - MQA sacrifices accuracy for speed, with ROUGE scores lower across all datasets compared to MHA.

4.2.2 Why is MQA Faster?

- MQA shares key-value pairs across multiple query heads, reducing computation in transformer layers.
- This reduces memory usage and speeds up token generation, particularly for short-form text like news summarization.

4.2.3 Why is MHA More Accurate?

- MHA has separate key-value pairs for each attention head, allowing it to capture more diverse relationships in text.
- This leads to better quality summaries, particularly for complex, long-form documents (arXiv, PubMed).

4.2.4 Real-World Implications

- MQA is ideal for real-time applications where speed is critical (e.g., chatbot responses, live summarization).
- MHA remains better for high-quality summarization tasks where accuracy is more important than speed (e.g., scientific summarization, legal document processing).

4.3 Summary of Results

Table No 4

Factor	MHA	MQA
Inference Speed	Slower	Faster
Accuracy (ROUGE)	Higher	Lower
Best for Short Texts?	No	Yes
Best for Long Texts?	Yes	No
Memory Usage	Higher	Lower
Ideal Use Case	High-accuracy summarization	Real-time applications

5. Discussion

This section compares our findings with existing literature, critically analyzes the results, and discusses the broader implications of using Multi-Query Attention (MQA) in comparison to Multi-Head Attention (MHA) for summarization tasks.

5.1 Comparison with Existing Literature

Our study builds upon the research of Ainslie et al. (2023), which introduced Grouped-Query Attention (GQA) and Multi-Query Attention (MQA) as efficient alternatives to Multi-Head Attention (MHA). The key claims from the original paper include:

- MQA significantly reduces inference latency compared to MHA.
- GQA balances efficiency and accuracy by grouping query heads.
- MQA performs slightly worse in accuracy but achieves major speed gains.

Our study partially confirms these claims but also introduces new insights:

Table No 5

Aspect	Original Paper (Ainslie et al., 2023)	Our Study (New Insights)
Evaluation Scope	MQA, GQA, MHA	MQA vs. MHA only
Datasets Used	NLP tasks (QA, Translation)	Summarization datasets (CNN/DailyMail, arXiv, PubMed)
Speed Findings	MQA is faster	Confirmed, but depends on dataset
Accuracy Findings	MQA is slightly worse	Confirmed, but accuracy gap is larger in summarization
Hardware Used	High-end GPUs	Mac M2 Max (consumer hardware)
GQA Results	GQA balances speed C accuracy	Not tested in our study

Key Difference: Unlike the original paper, we focused only on MQA vs. MHA and tested summarization models on consumer-grade hardware (Mac M2 Max) instead of high-end GPUs.

5.2 Critical Analysis of Results

5.2.1 Why is MQA Faster?

- MQA shares key-value pairs across query heads, which reduces computation and speeds up inference.
- On shorter texts (CNN/DailyMail), MQA achieves ~40% faster inference than MHA.
- However, for longer documents (arXiv, PubMed), MQA's speed advantage decreases, suggesting that MQA's efficiency gains may be task-dependent.

5.2.2 Why is MQA Less Accurate?

- MHA has separate key-value pairs for each attention head, which captures more detailed contextual relationships.
- MQA's shared key-value pairs lead to a loss of information, reducing accuracy in complex summarization tasks.
- Our results show that MQA has significantly lower ROUGE scores, which contradicts the original paper's claim that accuracy loss is minimal.

5.2.3 Does MQA Work Better for Short Texts?

- Yes, MQA shows the biggest improvement on CNN/DailyMail, which consists of shorter articles.
- For longer documents (arXiv, PubMed), MQA does not provide significant speed improvements and suffers a larger accuracy drop.

5.3 Implications and Significance of Findings

5.3.1 Implications for Model Deployment

- MQA is more efficient for resource-constrained environments like mobile devices and edge computing.
- MHA is preferred for applications requiring high-accuracy text generation, such as research papers or legal document summarization.
- Developers can choose MQA for speed or MHA for accuracy, depending on the use case.

5.3.2 Impact on Real-World Applications

- News summarization (e.g., CNN/DailyMail): MQA is a good choice since real-time summarization is required.
- Scientific document summarization (e.g., arXiv, PubMed): MHA is better due to its superior accuracy.
- Legal text summarization: MHA should be used as accuracy is crucial.
- Chatbot and real-time response systems: MQA is ideal for quick responses with minimal computation.

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