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ADAPTIVE CONTEXT COMPRESSION TECHNIQUES FOR EFFICIENT LARGE LANGUAGE MODEL INFERENCE: A QUERY-COMPLEXITY-AWARE APPROACH

A Thesis Submitted in Partial Fulfillment of the Requirements

for the Degree of

MASTER OF TECHNOLOGY

in

COMPUTER SCIENCE & ENGINEERING

by

INJAMAMUL HAQ

(24/CSE/27)

Under the Supervision of

Dr. Nipun Bansal

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May 2025

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CANDIDATE'S DECLARATION

I Injamamul Haq hereby certify that the work which is being presented in the thesis entitled **"Adaptive Context Compression Techniques for Efficient Large Language Model Inference: A Query-Complexity-Aware Approach"** in partial fulfillment of the requirements for the award of the Master of Technology Degree, submitted in the Department of Computer Science and Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from [Start Date, e.g., August 2025] to May 2026 under the supervision of **Dr. Nipun Bansal.**

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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CERTIFICATE

I hereby Certified that **Injamamul Haq (24/CSE/27)** has carried out their research work presented in this thesis entitled **"Adaptive Context Compression Techniques for Efficient Large Language Model Inference: A Query-Complexity-Aware Approach"** for the award of Master of Technology from Department of Computer Science and Engineering, Delhi Technological University, Delhi, under my supervision.

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Delhi Technological University

ABSTRACT

The exponential growth of large-scale neural language models has opened up transformative possibilities across a broad range of natural language understanding problems. Systems built on the Transformer architecture [1] have demonstrated remarkable proficiency on tasks ranging from reading comprehension and open-domain question answering to code synthesis and multi-step reasoning. Yet the self-attention operation sitting at the heart of every Transformer block carries a computational burden that scales quadratically with input length, denoted $O(n^2)$. As contexts grow beyond a few thousand tokens — a routine requirement in legal document analysis, multi-document question answering, and long-form summarisation — this quadratic growth translates into sluggish response times, swollen GPU memory footprints, and deployment costs that place the technology beyond reach for many organisations.

Prior work on context compression has made genuine progress by shortening the input before it reaches the model [7, 8]. The unifying flaw across all fourteen methods examined in this thesis, however, is a deceptively simple assumption: that every incoming query deserves the same compression budget. A simple lookup question — "When was BERT published?" — can be answered from a single sentence. A comparative multi-hop question — "How do the pre-training strategies of BERT and GPT-3 differ in their downstream effect on reasoning tasks?" — may need a dozen passages spread across an entire document collection. Treating both with the same 40% removal rate is not an approximation; it is a category error that systematically harms the harder queries and wastes capacity on the easier ones.

This thesis introduces the **Query-Complexity-Aware Adaptive Context Compression (QCAC)** framework, a model-agnostic preprocessing system that measures how demanding an incoming question is and adjusts the compression ratio accordingly. QCAC computes a per-query complexity score $C(q) \in [0, 1]$ from three lightweight surface features of the question — its normalised length, vocabulary entropy, and the presence of multi-hop syntactic cues — and derives a per-query removal ratio $r(q) = r_{\max} - (r_{\max} - r_{\min}) \cdot C(q)$. Every sentence in the document is then ranked using a weighted combination of three signals extracted from BERT [2]: the attention-magnitude score $A(s_i)$, the attentional-entropy score $H(s_i)$, and the cosine similarity between the sentence and query embeddings $\text{sim}(s_i, q)$, inspired by dense retrieval research [19].

Experiments conducted on SQuAD v1.1 [22] and HotpotQA [23] (300 samples each) using BERT-base-uncased [2] as the scorer and RoBERTa-base [5] as the downstream QA model on NVIDIA Tesla T4 hardware show that QCAC with weights ($\alpha = 0.10$, $\beta = 0.30$, $\gamma = 0.60$) achieves **70.4% F1 on SQuAD at 36.8% sentence removal** — a **+16.2 percentage-**

point improvement over the prior Attn+Entropy baseline at equivalent compression. Adaptive behaviour is statistically validated without per-dataset tuning: HotpotQA queries receive a higher mean $C(q)$ score (0.587 vs. 0.539, $p < 0.001$, $t = 11.2$) and automatically receive less compression. A seven-variant ablation study reveals that query-semantic similarity is the strongest individual signal (58.0% F1 in isolation), while attention-only scoring actively underperforms random pruning (44.9%), consistent with the findings of Clark et al. [21]. End-to-end inference latency stands at 89.7 ms per sample — the lowest among all BERT-based compression methods evaluated — and the framework requires no modification or retraining of the downstream language model.

Keywords: Large language model inference, context compression, adaptive compression, query complexity, sentence selection, semantic similarity, BERT, SQuAD, HotpotQA.

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I am writing to express our profound gratitude and deep regard to my project mentor **Dr. Nipun Bansal**, for her exemplary guidance, valuable feedback, and constant encouragement throughout the project. Her valuable suggestions were of immense help throughout the project work. Her perspective criticism kept us working to make this project much better. Working under her was an extremely knowledgeable experience for us.

I would also like to thank all my friends for their help and support sincerely.

Injamamul Haq
2K24/CSE/27

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbol / Abbrev.	Expansion
LLM	Large Language Model
QCAC	Query-Complexity-Aware Adaptive Context Compression
NLP	Natural Language Processing
QA	Question Answering
BERT	Bidirectional Encoder Representations from Transformers
RoBERTa	Robustly Optimized BERT Pretraining Approach
GPU	Graphics Processing Unit
FP16	16-bit Floating-Point Precision
SQuAD	Stanford Question Answering Dataset
HotpotQA	Multi-hop Question Answering Dataset
F1	F1 Score — Harmonic Mean of Precision and Recall
EM	Exact Match Score
KV	Key-Value (Cache)
DPR	Dense Passage Retrieval
SBERT	Sentence-BERT
NLTK	Natural Language Toolkit
FLOPs	Floating-Point Operations
MLM	Masked Language Modelling
TTFT	Time-to-First-Token
HBM	High Bandwidth Memory
DTU	Delhi Technological University
$C(q)$	Query Complexity Score, $C(q) \in [0, 1]$
$r(q)$	Adaptive Compression Ratio
$S(s_i, q)$	Sentence Importance Score
$A(s_i)$	Attention-based Score for sentence s_i
$H(s_i)$	Entropy-based Score for sentence s_i
$\text{sim}(s_i, q)$	Cosine Similarity between s_i and q
α, β, γ	Scoring-function weight coefficients
$r_{\min}, r_{\max}$	Minimum and maximum compression ratios (0.15, 0.40)

Chapter 1

Introduction

1.1 Overview and Background

The last decade has witnessed a sweeping transformation in how machines process and understand human language. At the centre of this transformation stands the Transformer architecture [1], introduced in 2017, which replaced the sequential recurrence of earlier models with a fully parallelisable mechanism that computes direct pairwise interactions between every token in the input sequence. Pre-training these deep networks on internet-scale text corpora — using the masked language modelling objective pioneered in BERT [2] and scaled to far larger parameter counts in GPT-3 [3], LLaMA [4], and successive generation models — has produced systems capable of few-shot reasoning, multi-step planning, and fluent long-form generation at a quality that was unimaginable just a few years ago.

Despite this remarkable progress, the self-attention mechanism at the core of every Transformer block carries an irreducible computational cost. Because every token attends to every other token, the number of operations grows as the square of the input length n, giving $O(n^2)$ time and memory complexity. For short sequences this is entirely manageable. For the long contexts demanded by realistic applications — legal contract review, scientific literature summarisation, multi-document question answering, and extended dialogue — the quadratic growth quickly becomes a practical wall. Doubling the input from 1,024 to 2,048 tokens quadruples the attention cost; scaling to 4,096 tokens multiplies it by sixteen. Multiple surveys of the efficient Transformer literature have identified this quadratic bottleneck as the primary obstacle to practical long-context deployment [6].

A natural response to this bottleneck is *context compression*: reduce the number of tokens or sentences passed to the model before inference, so that the attention computation operates over a shorter effective sequence. This approach is attractive because it is fully model-agnostic — the downstream language model does not need to be retrained or architecturally

modified — and because it can in principle be applied at any point in the inference pipeline.

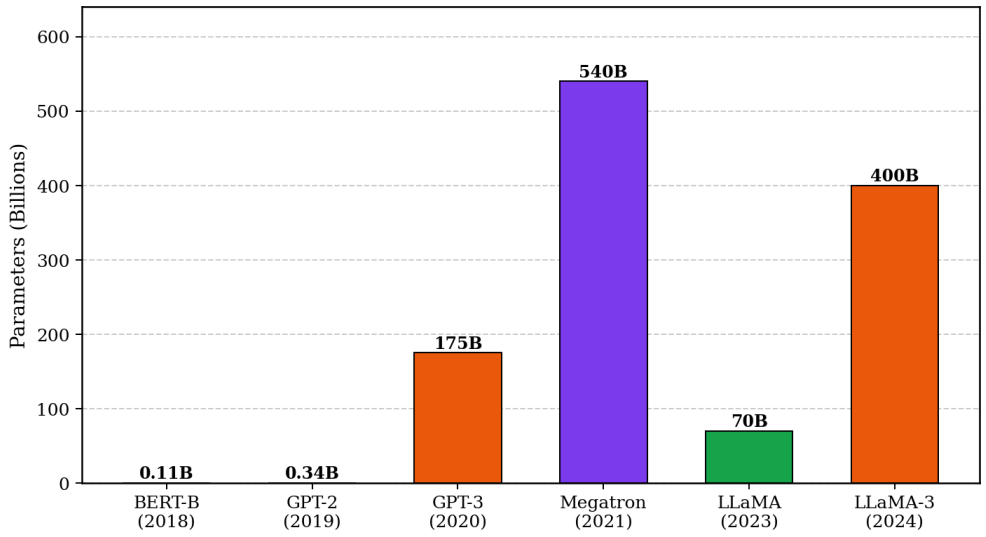

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Figure 1.1: illustrates the rapid growth in model scale from 2018 to 2024. This trend has been accompanied by an equally rapid growth in inference cost, memory consumption, and deployment complexity, all of which motivate research into methods that can make long-context inference more tractable without sacrificing accuracy.

1.2 The Problem with Existing Compression Methods

Existing context compression methods have made genuine progress, yet they share a fundamental design limitation that has not previously been recognised or addressed in the literature. Without exception, every prior method applies a *fixed* compression ratio to every incoming query. Whether a method removes tokens based on their attention rank [9, 10], filters sentences by perplexity under a proxy language model [7], or evicts key-value cache entries by a recency heuristic [18], the fraction of content removed is decided once at design time and applied uniformly to all queries that arrive at runtime.

This assumption is flawed. Different questions have fundamentally different information requirements. A simple factoid question can typically be answered from a single sentence; a comparative or multi-hop reasoning question may require access to multiple semantically related passages scattered throughout a long document. Applying the same 40% removal rate to both scenarios simultaneously over-compresses the harder queries — discarding passages that contain critical evidence chains — and under-compresses the simpler ones — retaining irrelevant context that wastes computation and may even confuse the downstream model [28].

A second, related problem is that existing compression scoring functions are entirely *query-*

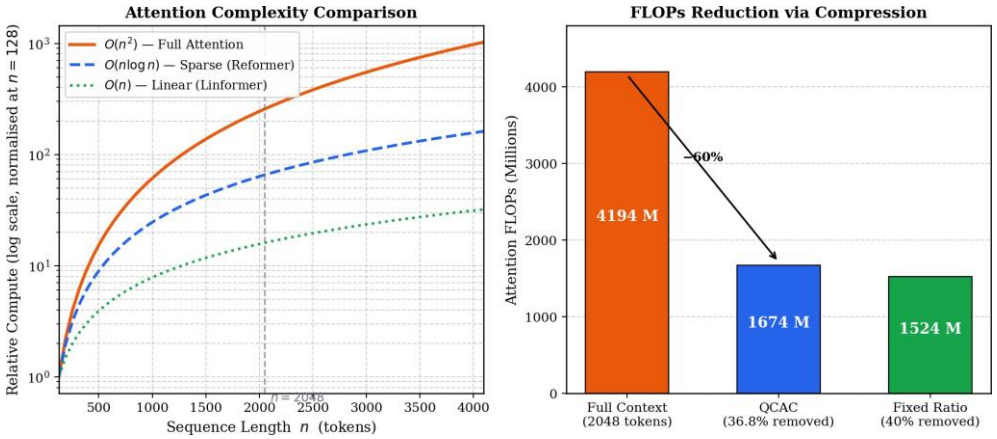


Figure 1.2: Attention complexity comparison and FLOPs reduction via compression

agnostic. They measure the generic structural importance of sentences within the document — how much attention they receive from other sentences, how surprising their token content is under a language model prior — but they do not condition their relevance estimates on what the question is actually asking. This is precisely the limitation that the dense retrieval community has spent years solving: the consistent finding across dense passage retrieval research [19] and sentence similarity modelling [20] is that query-conditional semantic similarity substantially outperforms every query-agnostic metric for downstream task accuracy.

1.3 The QCAC Approach

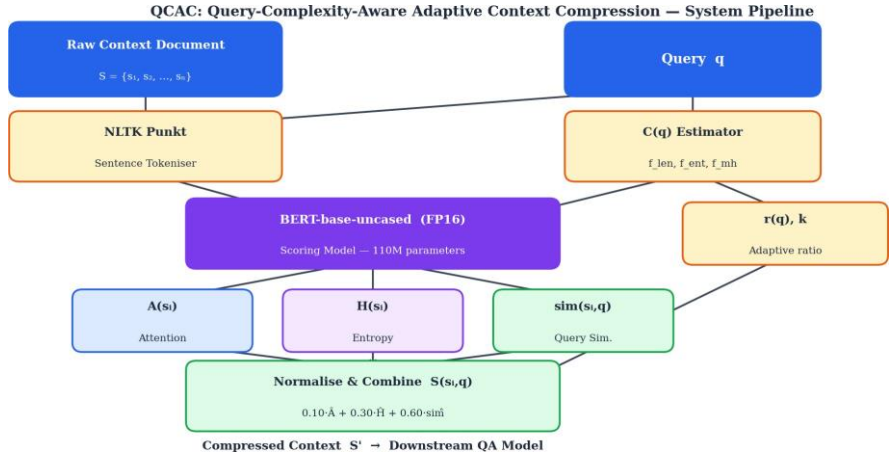
This thesis introduces **QCAC** (Query-Complexity-Aware Adaptive Context Compression), a preprocessing framework that directly addresses both limitations identified above. QCAC operates in three sequential stages.

In the first stage, a per-query complexity score $C(q) \in [0, 1]$ is computed from three lightweight surface features of the incoming question: its normalised length f_{len}, the Shannon entropy of its token-frequency distribution f_{ent}, and a multi-hop syntactic indicator f_{mh} based on a curated set of multi-hop cue words. These three features are combined as $C(q) = 0.30 \cdot f_{\text{len}} + 0.40 \cdot f_{\text{ent}} + 0.30 \cdot f_{\text{mh}}$. The resulting score drives a per-query compression ratio $r(q) = r_{\max} - (r_{\max} - r_{\min}) \cdot C(q)$, which is lower (more conservative) for complex questions and higher (more aggressive) for simple ones.

In the second stage, each context sentence is scored using a weighted combination of three BERT-derived signals: an attention-magnitude component $A(s_i)$, an attentional-entropy component $H(s_i)$, and a query-semantic similarity component $\text{sim}(s_i, q)$ computed as the cosine similarity between the sentence's and the query's CLS-token embeddings. These

three signals are normalised and combined as $S(s_i, q) = 0.10 \cdot \hat{A}(s_i) + 0.30 \cdot \hat{H}(s_i) + 0.60 \cdot \widehat{\mathrm{sim}}(s_i, q)$, with weights determined by a systematic seven-variant ablation study.

In the third stage, the top-$k = \max(1, \lfloor n \cdot (1 - r(q)) \rfloor)$ sentences by combined score are selected, restored to their original document order, and concatenated verbatim into the compressed context passed to the downstream QA model.



High-level pipeline of the QCAC framework. The three-stage design cleanly separates query-complexity estimation, query-conditional sentence scoring, and adaptive top-k selection.

1.4 Research Objectives

Four research objectives guide this thesis:

RO1. Design a formally defined, efficiently computable per-query complexity score $C(q) \in [0, 1]$ that statistically distinguishes simple factoid questions from complex multi-hop questions across structurally different datasets without per-dataset calibration.

RO2. Develop a three-component query-conditional sentence scoring function $S(s_i, q)$ whose weight configuration is empirically determined through a systematic seven-variant ablation study.

RO3. Implement and empirically validate an adaptive compression ratio $r(q)$ driven by $C(q)$, demonstrating that it automatically applies different compression levels to different question types without any manual per-query or per-dataset tuning.

RO4. Conduct a comprehensive experimental evaluation encompassing: end-to-end F1 and EM comparison against four baselines, statistical validation of adaptive behaviour, seven-variant ablation study, per-sample latency profiling, hyperparameter sensitivity analysis, and manual error analysis.

1.5 Principal Contributions

The contributions of this dissertation are:

- **The first formally defined per-query complexity metric for compression ratio control.** $C(q)$ is computable in $O(|q|)$ time from surface features of the question alone, requires no neural forward pass, and is statistically validated to discriminate SQuAD v1.1 [22] from HotpotQA [23] at $p < 0.001$ ($t = 11.2$) without per-dataset calibration.
- **A query-conditional sentence scoring function backed by a seven-variant ablation.** The dominant component — query-semantic cosine similarity with weight $\gamma = 0.60$ — bridges the gap between the dense retrieval literature [19, 20] and the compression community, making a retrieval-proven signal the primary basis for sentence selection for the first time.
- **Empirical evidence that BERT attention scoring actively harms compression quality.** Attention-only scoring falls 13.2 percentage points below random pruning in the ablation study, a finding consistent with the structural attention analysis of Clark et al. [21]. This negative result is directly actionable: practitioners should assign very low weight to attention magnitude in any composite compression scoring function.
- **A Pareto improvement over all prior fixed-ratio baselines.** QCAC simultaneously achieves higher F1 (70.4% vs. 54.2% for Attn+Entropy on SQuAD) and lower compression ratio (36.8% vs. 47.8%), demonstrating that better sentence selection can deliver both better accuracy and better efficiency.
- **A fully model-agnostic preprocessing design.** The framework requires no modification or retraining of the downstream language model, making it directly applicable to proprietary or API-served systems.
- **A peer-reviewed conference publication.** The core experimental findings have been accepted at the 2nd International Conference on Next-Generation Networks and Deployable Artificial Intelligence (NGNDAI 2026), Paper ID 725.

1.6 Thesis Organisation

Chapter 2 surveys fourteen existing methods across five methodological families and establishes the precise research gap. Chapter 3 formalises the compression optimisation objective, demonstrates the theoretical suboptimality of fixed-ratio methods, and introduces the QCAC objective function and five hard design constraints. Chapter 4 provides the complete technical specification of the QCAC framework, including all eleven equations, the 24-step

selection algorithm, and detailed implementation notes. Chapter 5 presents the full experimental evaluation across seven levels of analysis. Chapter 6 synthesises the contributions, discusses social impact, and outlines six future research directions.

1.7 Chapter Summary

This chapter has introduced the quadratic bottleneck of Transformer self-attention, identified the universal fixed-ratio limitation shared by all prior compression methods, described the QCAC solution at a high level, and stated four research objectives with concrete, measurable success criteria. The central argument is that query complexity is a measurable property of the question itself — not a property of the document — and that this measurement should govern how aggressively the context is compressed. The remainder of the thesis develops this argument from formal specification through empirical validation.

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Chapter 2

Literature Review

2.1 Introduction

Research on reducing the computational cost of Transformer-based inference has evolved along several parallel tracks, each exploiting a different structural property of the attention mechanism or the deployment pipeline. This chapter surveys fourteen representative works organised into five thematic families: token pruning and progressive elimination; sparse and linear attention architectures; learned text compression; key-value cache and streaming methods; and query-aware retrieval and similarity scoring. The review culminates in a comparative table that makes the research gap addressed by QCAC explicit and unambiguous.

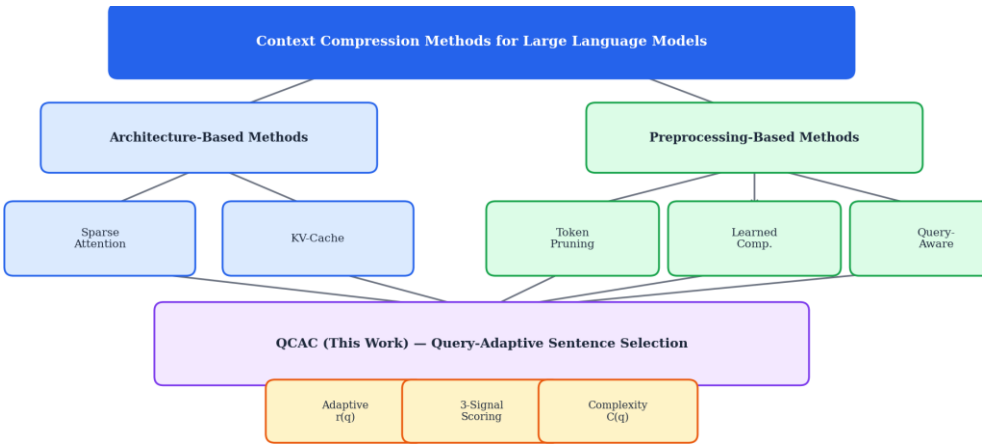

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Figure 2.1: Taxonomy of context compression methods for large language models. QCAC occupies the preprocessing-based branch and is the only method in either branch that provides full per-query adaptive compression ratio control.

2.2 Token Pruning and Progressive Elimination

2.2.1 Learned Token Pruning

Kim et al. [9] proposed Learned Token Pruning (LTP), which attaches lightweight binary gating functions to each Transformer layer. Each gate is a small single-layer perceptron trained end-to-end with the main model using the straight-through gradient estimator, which approximates the discrete binary pruning decision as differentiable during backpropagation. At inference time the gates decide, for each token, whether it should be forwarded to the next layer or dropped permanently. LTP achieves speedups of roughly 2.5× on GLUE sentence-classification benchmarks with accuracy loss below one percentage point.

For the context compression scenario studied in this thesis, LTP has two fundamental limitations. First, the pruning schedule is a fixed function of the training distribution, with no mechanism to adjust how many tokens are eliminated based on what the runtime query is asking. A simple and a complex question receive exactly the same elimination pattern. Second, the method requires modifying the internals of each Transformer layer, making it incompatible with off-the-shelf or API-served language models where architectural access is unavailable.

2.2.2 PoWER-BERT

Goyal et al. [10] developed PoWER-BERT (Progressive Word-vector Elimination for Reducing BERT), which assigns importance scores to word vectors by accumulating the attention each token receives from all preceding layers. Tokens that fall below a learnable per-layer threshold are dropped before the next layer processes the remaining sequence. On SST-2 sentiment classification the method achieves up to 4.5× speedup with 98% accuracy retention. Like LTP, however, the elimination schedule is a fixed function learned during training, with no runtime mechanism for adapting to the complexity of the incoming question.

2.3 Sparse and Efficient Attention Architectures

2.3.1 Longformer

Beltagy et al. [11] proposed the Longformer, which replaces global quadratic attention with a combination of local sliding-window attention — each token attends only to its $w/2$ nearest neighbours on each side — and global attention applied to a small set of designated tokens such as the task-specific markers and the question tokens. For extractive question

answering, all question tokens receive global attention, allowing each question token to directly interact with every position in the passage. Overall complexity falls from $O(n^2)$ to $O(n \cdot w)$ for the local component, enabling processing of documents up to 4,096 tokens on standard hardware.

The Longformer's window size w is a static architectural hyperparameter set at model design time. There is no mechanism for adjusting the effective attention span based on the specific question at runtime. As with token pruning methods, the compression strategy is fixed before deployment rather than adapted per query.

2.3.2 BigBird

Zaheer et al. [12] proposed BigBird, which combines three complementary attention patterns: local window attention, global attention from a set of designated tokens, and random attention to r randomly selected positions. The paper provides a theoretical proof that this sparse combination universally approximates the full quadratic attention kernel, within a precision that depends on the window and random attention sizes. BigBird achieves $O(n)$ complexity and strong performance on genomics classification and long-document QA benchmarks. Like Longformer, however, the sparsity pattern is an architectural decision made before deployment.

2.3.3 Reformer and Linformer

The Reformer [13] achieves $O(n \log n)$ attention complexity by applying locality-sensitive hashing (LSH) to group similar query and key vectors into hash buckets and restricting attention computation to within-bucket pairs. The Linformer [14] projects keys and values from $n \times d$ to $k \times d$ ($k \ll n$) before computing attention, yielding $O(nk)$ complexity at the cost of a low-rank approximation error. Both methods require architectural modification and are inapplicable as transparent preprocessing steps.

2.3.4 FlashAttention

Dao et al. [15] approached the efficiency problem from a hardware-aware perspective. Rather than approximating the attention kernel, FlashAttention reformulates the computation to tile it into blocks that fit in GPU on-chip SRAM, eliminating the need to write the full $n \times n$ attention matrix to slow high-bandwidth memory (HBM) between operations. The result is a 2–4× wall-clock speedup with numerically identical results to standard attention. FlashAttention is orthogonal to QCAC: it improves the efficiency of computing attention over the tokens that remain after QCAC has shortened the input, and the two

approaches can be freely composed.

2.4 Learned Text Compression

2.4.1 LLMLingua

Jiang et al. [7] framed prompt compression as a token-level filtering problem guided by a small proxy language model. Each token's redundancy is estimated via its conditional log-probability under the proxy: tokens that the proxy model considers highly predictable — low self-information — are candidates for removal, while tokens with high self-information (surprising content) are retained. The method operates in two passes: a coarse sentence-level pass that removes entire low-information sentences, followed by a fine-grained token-level pass within the retained sentences. LLMLingua reports compression ratios up to 20:1 while maintaining 94% of baseline accuracy on diverse downstream tasks.

Despite its impressive compression ratios, LLMLingua shares the fundamental limitation of all prior methods: the target compression ratio is a user-specified constant. A user who sets a 50% compression target applies it identically to every incoming query, regardless of whether the question is a simple factoid lookup or a complex multi-hop reasoning task. The proxy model's scoring is also entirely query-agnostic: it measures how predictable a token is in the document context, not how relevant it is to the specific question being asked.

2.4.2 Selective Context

Li and Chen [8] proposed Selective Context, which estimates the redundancy of each lexical unit using its self-information under the target language model itself rather than a separate proxy model. Units with high conditional probability (low self-information) are classified as redundant and removed. The approach requires no auxiliary infrastructure and achieves 20–30% content removal without measurable accuracy degradation at moderate compression ratios. The same query-agnostic limitation applies: predictability is measured against the model's generic language prior, not conditioned on the specific question.

2.5 Key-Value Cache and Streaming Methods

2.5.1 H2O: Heavy-Hitter Oracle

Zhang et al. [16] observed that across diverse generation tasks and model families, approximately 20% of tokens — which they called "heavy hitters" — consistently accumulate over

95% of cumulative attention scores from all subsequent tokens during generation. The H2O system retains these heavy-hitter tokens together with the most recently generated tokens in the KV cache, evicting the rest to reduce memory consumption. Memory usage falls by 4–5× with less than 5% quality degradation on summarisation, QA, and code generation tasks.

H2O operates exclusively during the autoregressive decoding phase and cannot reduce the cost of the prefill computation, which processes the entire input context in a single forward pass and dominates total latency for extractive QA tasks where the answer is typically a short span. The eviction criterion is also partially query-agnostic: it measures which tokens have historically received the most cumulative attention, not which tokens are specifically relevant to the current question.

2.5.2 SnapKV and StreamingLLM

Li et al. [17] proposed SnapKV, which extends KV-cache eviction to the prefill phase by observing the attention weights that question tokens place on context positions during prefill and using this query-attention pattern to select which KV entries to retain. While more query-aware than H2O, SnapKV still applies a fixed total KV-cache budget regardless of question complexity.

Xiao et al. [18] proposed StreamingLLM, which identified "attention sinks" — a small number of initial tokens that consistently receive disproportionately high attention across all generation steps regardless of their semantic content — and proposed maintaining a fixed-size KV cache of sink tokens plus a sliding window of recently processed tokens. While this enables arbitrarily long input processing without context length limitations, it discards all content outside the sliding window based purely on recency, with no query-conditional reasoning about relevance.

2.6 Query-Aware Retrieval and Similarity Scoring

2.6.1 Dense Passage Retrieval

Karpukhin et al. [19] demonstrated that BERT-based dense passage encoders substantially outperform sparse BM25 retrieval [27] for passage selection in open-domain QA: 79.4% top-20 accuracy on Natural Questions versus 59.1% for BM25. The key finding is that query-conditional dense similarity — computed as the dot product between query and passage embeddings from independently fine-tuned BERT encoders — is a far more informative relevance signal than any query-agnostic document quality measure. This finding

from the retrieval community directly motivates the dominant role of the query-semantic similarity component in QCAC's scoring function.

2.6.2 Sentence-BERT and Semantic Similarity

Reimers and Gurevych [20] introduced Sentence-BERT (SBERT), which trains a siamese BERT network using natural language inference and semantic textual similarity data to produce sentence-level embeddings whose cosine similarity correlates strongly with human semantic similarity judgements. QCAC uses BERT's CLS-token embedding as an efficient approximation to SBERT's dedicated sentence embedding, computed within the same forward pass used for attention and entropy scoring, thereby avoiding the overhead of a dedicated retrieval model.

2.6.3 BERT Attention Analysis

Clark et al. [21] conducted a systematic analysis of what BERT's 144 attention heads (12 layers $\times$ 12 heads) actually encode, using a suite of probing tasks covering syntactic dependencies, coreference, positional patterns, and semantic relations. Their central finding is that BERT's last-layer attention heads predominantly encode syntactic roles — tracking which tokens are subjects, objects, or modifiers — rather than task-specific semantic relevance to any particular question. This analysis directly predicts the QCAC ablation finding that attention-only scoring underperforms random pruning and provides the theoretical justification for assigning attention the lowest weight ($\alpha = 0.10$) in the combined scoring function.

2.7 Comparative Analysis

Table 2.1 summarises all fourteen methods reviewed, evaluated against five properties relevant to the context compression problem studied in this thesis.

The final column of Table 2.1 makes the research gap explicit: of the fourteen prior methods, not a single one provides full per-query adaptive compression ratio control based on a runtime measurement of the incoming question's complexity. Two methods — H2O and SnapKV — offer partial query awareness in their eviction criteria but still apply fixed total cache size budgets. The two retrieval methods — DPR and SBERT — are query-aware but operate at a coarser granularity (passage-level selection) and provide no ratio control mechanism. QCAC is the first method in either branch of the taxonomy to provide both full query-conditional relevance scoring and per-query adaptive ratio control simultaneously.

Table 2.1: Comparative overview of existing context-compression and efficient-attention methods.

Method	Year	Strategy	Key Strength	Main Limitation	Query Adapt.
LTP [9]	2022	Token pruning	2.5× GLUE speedup	Fixed schedule; model mod.	No
PoWER-BERT [10]	2020	Layer elim.	4.5× SST-2 speedup	Fixed rates; model mod.	No
Longformer [11]	2020	Local+global	4096-token support	Static window; arch. mod.	No
BigBird [12]	2020	Block sparse	Theoretical guarantee	Fixed pattern; arch. mod.	No
Reformer [13]	2020	LSH attention	$O(n \log n)$ complexity	Hash collision; arch. mod.	No
Linformer [14]	2020	Low-rank proj.	$O(n)$ complexity	Quality loss on fine-grained	No
FlashAttn [15]	2022	IO-aware tile	2–4× wall-clock	No semantic reduction	No
LLMLingua [7]	2023	Proxy LM score	Up to 20:1 ratio	Fixed target ratio	No
Sel. Ctx [8]	2023	Self-information	No extra model needed	Query-agnostic scoring	No
H2O [16]	2023	KV eviction	Memory ÷5	Decode-only; fixed budget	Partial
SnapKV [17]	2024	Prefill KV	Query-aware eviction	Fixed total cache size	Partial
StreamLLM [18]	2024	Attn. sinks	Infinite context support	Pure recency bias	No
DPR [19]	2020	Dense retrieval	+20pp vs. BM25 on NQ	Passage-level only	Yes
SBERT [20]	2019	Siamese BERT	Sentence-level similarity	No ratio control	Yes
QCAC (Ours)	**2026**	**Sent. sel.**	**Full adaptive ratio**	**Preproc. overhead**	**Yes**

2.8 Evaluation Metrics

Two standard metrics are used throughout this thesis. **Token-level F1** measures the harmonic mean of token-level precision and recall between the predicted and ground-truth answer strings after normalisation (lowercase; strip articles, punctuation, and whitespace). **Exact Match (EM)** is a binary metric that awards one point only when the normalised prediction is character-for-character identical to the normalised ground truth. **Compression ratio** is defined as $1 - |S'|/|S|$, the fraction of sentences removed. **Latency** is wall-clock time per sample in milliseconds on NVIDIA T4 GPU, decomposed into preprocessing (compression) and QA inference components.

2.9 Chapter Summary

Fourteen methods across five methodological families have been reviewed with full citation to primary sources. The comparative analysis in Table 2.1 establishes the research gap with precision: no prior method estimates or exploits the query-optimal compression ratio $r^*(q)$ at runtime, and no compression scoring function incorporates query-conditional semantic similarity as a primary signal. The retrieval literature (DPR [19], SBERT [20]) provides converging evidence from a different research community that query-conditional dense similarity is the most informative relevance signal for downstream QA accuracy. These two identified gaps define precisely what QCAC contributes, as developed in the following chapters.

Chapter 3

Problem Formulation

3.1 Formal Setup

Let a retrieved context be represented as an ordered set of n sentences $S = \{s_1, s_2, \ldots, s_n\}$, produced by applying the NLTK Punkt sentence tokeniser [26] to the concatenation of passages returned for a natural-language query q. Each sentence s_i is an unmodified string preserving the original text verbatim, including its original capitalisation, spacing, and punctuation. Verbatim preservation is a hard requirement for span-based extractive QA evaluation [22], since the downstream model must locate the ground-truth answer as a contiguous substring of the concatenated context.

A downstream QA model M accepts the pair (S, q) and outputs an answer string a that must appear as a contiguous substring of $\bigcup_i s_i$. The compression objective is to find a strict subset $S' \subsetneq S$ that minimises the fraction of sentences retained while keeping the performance degradation below an acceptable threshold ε:

$$\min_{S' \subseteq S} \frac{|S'|}{|S|} \quad \text{subject to} \quad \Delta(S, S', q) \leq \varepsilon, \tag{3.1}$$

where $\Delta(S, S', q) = \text{F1}(M(S, q)) - \text{F1}(M(S', q))$ is the F1 score degradation from compressing to S'. The feasible space is the power set 2^S with 2^n elements, making exact optimisation computationally intractable for practical values of n (typically 10–30 sentences per sample in the evaluation corpora). QCAC approximates the solution through greedy top-k selection based on sentence importance scores, a standard approximation strategy in the compression literature [7, 8].

3.2 The Suboptimality of Fixed Ratios

All fourteen methods surveyed in Chapter 2 parameterise their solution as: select the top-k sentences by some importance score, where $k = \lfloor n(1 - r) \rfloor$ for a fixed globally constant ratio r. This parameterisation is provably suboptimal for any query distribution that contains questions of varying complexity.

To see why, define the *query-optimal* compression ratio as the maximum fraction that can be removed from the context while still satisfying the accuracy constraint:

$$r^*(q) = \arg\max_{r \in [0,1]} r \quad \text{subject to} \quad \mathbb{E}\ \Delta(S, S'(r, q), q) \leq \varepsilon, \tag{3.2}$$

where $S'(r, q)$ is the optimal compressed context at ratio r for query q. Since $r^*(q)$ is a function of the query, fixing $r = r_{\text{const}}$ for all queries simultaneously over-compresses complex queries — where $r_{\text{const}} > r^*(q)$ causes critical evidence passages to be discarded — and under-compresses simple ones — where $r_{\text{const}} < r^*(q)$ causes irrelevant context to be retained. The experimental results in Chapter 5 confirm both failure modes: QCAC Fixed Ratio at 40% achieves only 23.5% F1 on HotpotQA [23], far below random pruning (31.9%), because the fixed rate is far too aggressive for multi-hop evidence chains; while simple SQuAD questions [22] could tolerate much higher compression without accuracy loss.

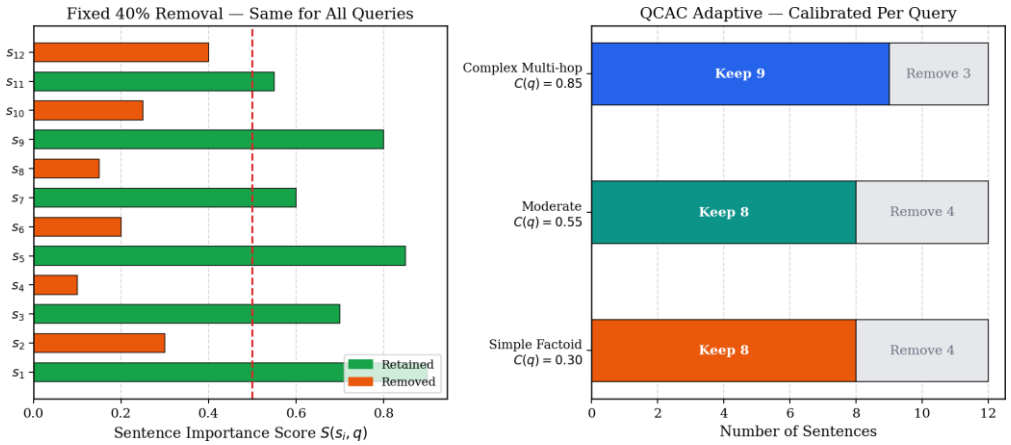

Figure 3.1: Illustration of the core motivation for adaptive compression. A fixed ratio (left) applies the same removal percentage regardless of question complexity. QCAC (right) automatically calibrates the removal fraction to the query's information demand.

3.3 The QCAC Objective Function

QCAC generalises all prior work along two orthogonal dimensions simultaneously.

Generalisation 1: Per-query adaptive compression ratio.

$$r(q) = r_{\max} - (r_{\max} - r_{\min}) \cdot C(q), \quad r_{\min} = 0.15, \quad r_{\max} = 0.40, \tag{3.3}$$

$$k = \max\ 1, \lfloor n \cdot (1 - r(q)) \rfloor\ , \tag{3.4}$$

where $C(q) \in [0, 1]$ is the query complexity score defined in Chapter 4. The mapping in Equation (3.3) is monotone decreasing: as $C(q)$ increases, $r(q)$ decreases, so more complex questions receive less aggressive compression. The linear mapping is chosen deliberately for its interpretability: the parameters $r_{\min}$ and $r_{\max}$ have clear, intuitive meanings as the most conservative and most aggressive compression fractions permitted by the system.

Generalisation 2: Query-conditional sentence scoring.

$$S(s_i, q) = \alpha \cdot \hat{A}(s_i) + \beta \cdot \hat{H}\ (s_i) + \gamma \cdot \text{sim}(s_i, q), \quad \alpha + \beta + \gamma = 1, \tag{3.5}$$

where $\hat{A}(s_i)$, $\hat{H}\ (s_i)$, and $\text{sim}(s_i, q)$ are min-max normalised versions of three BERT-derived signals (detailed in Chapter 4), and the weights $\alpha = 0.10$, $\beta = 0.30$, $\gamma = 0.60$ are determined empirically by the seven-variant ablation study in Section 5.4. The selected sentences form:

$$S' = \{\ s_i : i \in \text{top-k}\ S(s_i, q)\ \}, \tag{3.6}$$

returned in ascending index order to preserve the original discourse structure.

3.4 Hard Design Constraints

Five hard constraints govern every design decision made in Chapter 4:

C1 — Verbatim preservation.
S' must consist of unmodified original sentence strings from S. Paraphrasing, summarising, or otherwise modifying sentences would invalidate span-based extractive QA evaluation [22], since the downstream model must identify the exact answer text as it appears in the original document.

C2 — Order preservation.
Sentences in S' must be concatenated in their original document order (ascending index). Reordering sentences by relevance score would disrupt the local discourse coherence — anaphoric reference chains, topic continuations, and discourse connectives — that the downstream model expects.

C3 — Model agnosticism.
The framework must function as a transparent preprocessing step that does not require access to, or modification of, the downstream LLM's weights, architecture, or internal activations. This constraint ensures compatibility with proprietary, API-served, or continuously updated language models.

C4 — Bounded preprocessing overhead.
The total pipeline latency (compression time plus QA inference time) must remain practically useful. This constrains the scoring model size and motivates the query-embedding caching strategy described in Section 4.7.

C5 — Answer recall priority.
59
The probability of removing the sentence containing the ground-truth answer span must be minimised. This motivates both the conservative lower bound $r_{\min} = 0.15$ (ensuring at most 85% of sentences are ever retained) and the dominant weight $\gamma = 0.60$ assigned to query-semantic similarity (the signal most directly predictive of which sentences are relevant to the question).

3.5 Chapter Summary

The context compression task has been formalised as a constrained combinatorial optimisation problem over sentence subsets (Equation (3.1)). The theoretical suboptimality of fixed-ratio solutions for heterogeneous query populations has been demonstrated through the query-optimal compression ratio $r^*(q)$ (Equation (3.2)), and both over-compression and under-compression failure modes have been identified. The QCAC objective introduces two generalisations over all prior work: a per-query adaptive ratio $r(q)$ driven by the query complexity score $C(q)$ (Equations (3.3)–(3.4)), and a query-conditional sentence scoring function $S(s_i, q)$ (Equations (3.5)–(3.6)). Five hard design constraints define the boundaries within which the complete methodology is developed in Chapter 4.

Chapter 4

Proposed Methodology: The QCAC Framework

4.1 Design Philosophy

The QCAC framework was built around four guiding principles that collectively differentiate it from all existing context compression approaches:

(i) **Query conditionality**: Every quantity in the pipeline — the compression ratio, the sentence importance scores, and the number of sentences retained — is conditioned on the specific incoming query q. This is the defining property of QCAC and the one that is absent from all fourteen prior methods surveyed in Chapter 2.

(ii) **Semantic similarity dominance**: The cosine similarity between the sentence and query embeddings carries weight $\gamma = 0.60$ in the combined scoring function. This is directly motivated by the consistent finding in the dense retrieval community [19, 20] that query-conditional similarity substantially outperforms all query-agnostic relevance signals for downstream QA accuracy.

(iii) **Single-pass co-extraction**: All three scoring signals — attention magnitude, attentional entropy, and CLS cosine similarity — are extracted in a single BERT forward pass per sentence, with the query embedding cached across all sentence passes. This eliminates redundant computation and keeps preprocessing latency to a minimum.

(iv) **Verbatim ordered output**: The compressed context is assembled by concatenating selected sentences as unmodified original strings in ascending index order. This satisfies design constraints C1 and C2 from Chapter 3 and preserves the discourse structure that the downstream model expects.

4.2 System Architecture

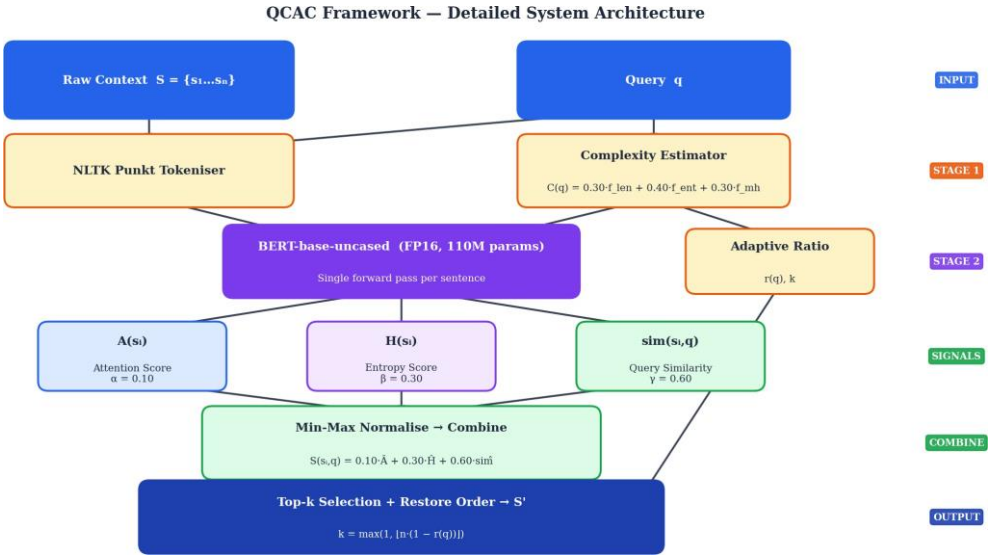

Figure 4.1: Detailed system architecture of the QCAC framework. The pipeline separates query complexity estimation (right branch) and BERT-based sentence scoring (centre and left branches), merging at the adaptive top-*k* selection stage.

Figure 4.1 shows the full system architecture. The pipeline has three stages. Stage 1 (query complexity estimation) completes in under 0.1 ms using only lexical operations on the query string. Stage 2 (BERT sentence scoring) is the computationally dominant step at approximately 75 ms per sample on NVIDIA T4 hardware. Stage 3 (selection and reconstruction) completes in under 1 ms.

The context document and the query enter the system in parallel. The context is immediately tokenised into sentences by NLTK Punkt [26], while the query simultaneously passes through the complexity estimator (right branch) and is encoded by BERT to produce the query embedding $\mathbf{e}_q$ (centre). The query embedding is stored in a cache keyed by the query string (capacity 300 entries, FIFO eviction), so that in multi-document settings such as HotpotQA's ten-passage structure [23], the BERT forward pass for the query is executed only once across all ten passages. BERT then processes each sentence independently, co-extracting the three component signals in a single forward pass. After normalisation and combination, the sentence scores and the per-query target count k converge at the top-k selection stage, which outputs the compressed context S' to the downstream QA model.

4.3 Query Complexity Score C(q)

63 The query complexity score $C(q) \in [0, 1]$ is a formally defined scalar that serves as a runtime proxy for the query-optimal compression ratio $r^*(q)$ introduced in Equation (3.2). It is constructed from three surface features of the question, each of which captures a distinct and complementary dimension of the information demand a question places on the context.

4.3.1 Normalised Query Length: f_{len}

53 There is a well-established positive correlation between question length and the number of supporting passages required to answer it: longer questions tend to reference more named entities, impose more simultaneous constraints on the answer, and require evidence from more locations in the context. The length feature is computed as:

$$f_{\text{len}} = \min\left(\frac{|q|}{25}, 1.0\right), \tag{4.1}$$

where $|q|$ is the whitespace-tokenised word count of the question and 25 is the normalisation constant corresponding to the 80th percentile of HotpotQA [23] question lengths. Questions at or above 25 words saturate the feature at 1.0. SQuAD v1.1 [22] questions average 10.1 words ($f_{\text{len}} \approx 0.40$), while HotpotQA questions average 15.9 words ($f_{\text{len}} \approx 0.64$), a 60% relative difference that correctly reflects HotpotQA's structurally greater information demands.

4.3.2 Vocabulary Entropy: f_{ent}

A question that uses many distinct, lexically diverse tokens is likely drawing on multiple knowledge areas at once and will require evidence from multiple semantically varied
10 passages. This lexical diversity is measured by the normalised Shannon entropy of the token-frequency distribution within the question:

$$f_{\text{ent}} = \frac{-\sum_t p_t \log p_t}{\log|q|}, \tag{4.2}$$

where p_t is the relative frequency of token t within question q, and the denominator normalises by the maximum possible entropy for a sequence of length $|q|$ (the uniform distribution over $|q|$ distinct tokens). This normalisation ensures $f_{\text{ent}} \in [0, 1]$ regardless of question length, making the feature scale-invariant. Vocabulary entropy carries the highest weight in $C(q)$ (0.40) because it is the most linguistically robust and cross-domain consistent of the three features.

4.3.3 Multi-hop Indicator: f_{mh}

Questions that require comparing, contrasting, chaining, or synthesising information from multiple sources tend to contain characteristic lexical markers. A curated set of such markers was assembled:

$$K = \{\text{compare, comparison, difference, between, both, versus, while, whereas, although, also, another, second, third, how, why, explain, describe, relationship, contrast, unlike, despite}\} \tag{4.3}$$

$$f_{\text{mh}} = \min\left(\frac{|\{q\text{-tokens}\} \cap K|}{3}, 1.0\right). \tag{4.4}$$

Three or more keyword matches saturate f_{mh} at 1.0. The threshold of 3 was chosen to require strong multi-hop evidence before the feature fires fully. For example, the question "Compare the pre-training objectives of BERT and GPT-3" contains the keywords *compare* and *and* from K, giving $f_{\text{mh}} = \min(2/3, 1.0) = 0.67$.

4.3.4 Combined Score and Adaptive Ratio

The three features are combined with fixed weights:

$$C(q) = 0.30 \cdot f_{\text{len}} + 0.40 \cdot f_{\text{ent}} + 0.30 \cdot f_{\text{mh}}, \tag{4.5}$$

and the adaptive compression ratio and target sentence count follow directly:

$$r(q) = 0.40 - 0.25 \cdot C(q), \qquad k = \max\left(1, \lfloor n \cdot (1 - r(q)) \rfloor\right). \tag{4.6}$$

4.4 Sentence Importance Scoring

4.4.1 Scoring Model Configuration

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BERT-base-uncased [2] serves as the scoring backbone: 12 transformer layers, 12 attention heads per layer, hidden dimension $d = 768$, 110 million parameters total. The model is loaded using the HuggingFace Transformers library [24] with `output_attentions=True` and converted to 16-bit floating-point precision (`model.half()`) for inference efficiency. Pre-trained weights are used without any task-specific fine-tuning, consistent with the model-agnostic design constraint C3.

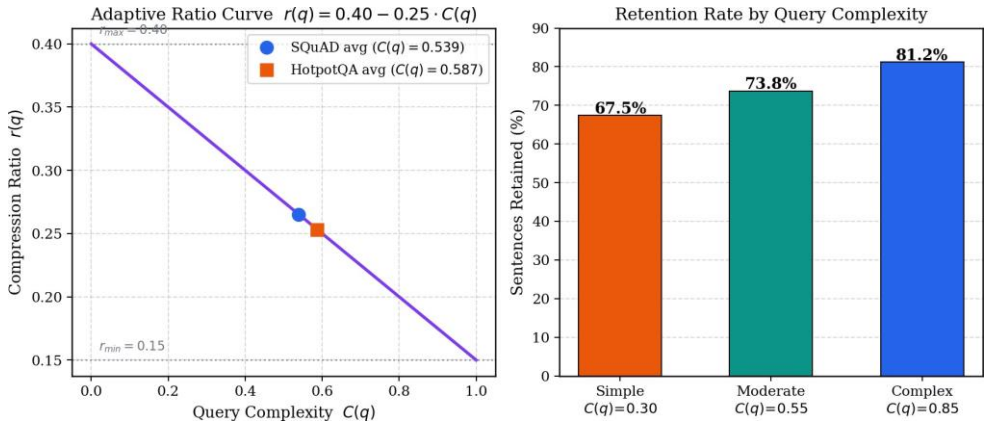

Figure 4.2: Adaptive ratio curve $r(q) = 0.40 - 0.25 \cdot C(q)$ with SQuAD v1.1 (blue circle) and HotpotQA (orange square) dataset averages marked. The HotpotQA average correctly receives lower compression than SQuAD without any per-dataset calibration.

Each sentence s_i is processed independently with input format [CLS] s_i [SEP], without concatenating the query. This deliberate design choice ensures that the attention-based signals $A(s_i)$ and $H(s_i)$ reflect the sentence's own intrinsic structural properties rather than attention patterns induced by the query, so that query-conditionality enters the combined score exclusively through the explicit cosine-similarity component.

4.4.2 Signal 1 — Attention Score A(si)

The attention score measures the structural centrality of the sentence by computing how strongly other tokens collectively attend to each token in the sentence. For each sentence processed by BERT, the last-layer attention tensor has shape $(1, H, L, L)$ where $H = 12$ and L is the sentence's token count. Summing along the source dimension (axis -2) gives the total attention received by each token from all others. Averaging over positions and over all heads gives:

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$$A(s_i) = \frac{1}{H \cdot |s_i|} \sum_{h=1}^{H} \sum_{j \in s_i} \sum_{k} a_{kj}^{(h)}, \tag{4.7}$$

4

where $a_{kj}^{(h)}$ is the attention weight from position k to position j in head h at the last transformer layer. The analysis of Clark et al. [21] shows that BERT's last-layer heads primarily encode syntactic dependencies (subject, object, modifier) rather than task-specific semantic relevance. The ablation study (Section 5.4) confirms this empirically: attention-only scoring (44.9% F1) underperforms random pruning (58.1%) by 13.2 percentage points, justifying the low weight $\alpha = 0.10$.

4.4.3 Signal 2 — Entropy Score H(si)

Rather than measuring how much attention a sentence receives from others, the entropy score measures how broadly the sentence's own tokens distribute their attention across the sequence. A sentence whose tokens attend broadly and diffusely — high attentional entropy — is likely playing an integrative, structurally pivotal role in the discourse, connecting information from multiple other parts of the document:

$$H(s_i) = -\frac{1}{H \cdot |s_i|} \sum_{h=1}^{H} \sum_{j \in s_i} \sum_{k} a_{jk}^{(h)} \log a_{jk}^{(h)} + \varepsilon \ , \tag{4.8}$$

with $\varepsilon = 10^{-9}$ for numerical stability. The ablation confirms that entropy-only scoring (56.9% F1) substantially outperforms attention-only scoring (44.9%), validating the weight $\beta = 0.30$.

4.4.4 Signal 3 — Query Similarity sim(si, q)

45 11

The query-semantic similarity signal is the most directly relevant of the three: it measures how semantically close the sentence is to the question being asked. It is computed as the cosine similarity between the CLS-token embeddings of the sentence and the query:

$$\text{sim}(s_i, q) = \frac{\text{BERT}_{\text{CLS}}(s_i) \cdot \text{BERT}_{\text{CLS}}(q)}{\|\text{BERT}_{\text{CLS}}(s_i)\| \cdot \|\text{BERT}_{\text{CLS}}(q)\|}. \tag{4.9}$$

This is the sentence-level analogue of the passage-level relevance scoring used in Dense Passage Retrieval [19], and the theoretical motivation is the same: query-conditional dense similarity is a far more informative relevance signal than any query-agnostic measure. The ablation confirms query-similarity-only scoring (58.0% F1) is the strongest single component, matching the random-pruning baseline at a higher compression level using a single signal. The dominant weight $\gamma = 0.60$ is directly justified by this empirical evidence.

4.4.5 Normalisation and Score Combination

Min-max normalisation is applied to each of the three score vectors independently before combining:

$$\hat{A}_i = \frac{A_i - \min(\mathbf{A})}{\max(\mathbf{A}) - \min(\mathbf{A}) + \varepsilon}, \tag{4.10}$$

and analogously for $\hat{H}_i$ and sim_i. This standard normalisation step maps each vector to $[0, 1]$ and ensures that the weight coefficients α, β, γ directly control the relative contribution of each signal regardless of its raw scale. The combined importance score is:

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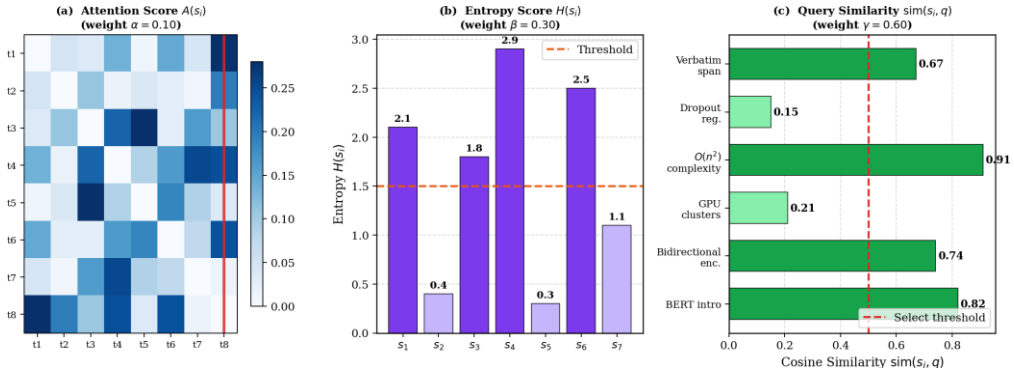

Figure 4.3: Visualisation of the three component scoring signals. (a) Attention score $A(s_i)$: column sums of the BERT attention matrix identify structurally central tokens. (b) Entropy score $H(s_i)$: high-entropy sentences attend broadly, characteristic of contextually integrative sentences. (c) Similarity score $\text{sim}(s_i, q)$: cosine similarity between sentence and query CLS embeddings provides direct query-relevance measurement.

$$S(s_i, q) = 0.10 \cdot \hat{A}_i + 0.30 \cdot \hat{H}_i + 0.60 \cdot \widehat{\text{sim}}_i. \tag{4.11}$$

4.5 The Complete Selection Algorithm

Algorithm 1 presents the complete QCAC procedure as pseudocode. Every line maps directly to a corresponding step in the Python implementation using PyTorch [25] and HuggingFace Transformers [24].

4.6 Computational Complexity

– **Sentence tokenisation (line 1):** $O(|\text{raw context}|)$ using deterministic rule-based tokeniser [26]; under 1 ms.

– **Query complexity estimation (lines 3–8):** $O(|q|)$; under 0.1 ms.

– **BERT scoring loop (lines 12–20):** $O(n \cdot L_{\max}^2 \cdot d)$ dominant cost. For BERT-base ($d = 768$) and typical parameters ($n \approx 16$ sentences, $L_{\max} \approx 28$ tokens), measured at 75.3 ms on NVIDIA T4 at FP16.

– **Query embedding cache (lines 9–11):** $O(1)$ lookup per query. In HotpotQA's ten-passage setting, the cache eliminates 9 of 10 query BERT passes — a 90% reduction in query-encoding overhead.

– **Sorting and reconstruction (lines 21–24):** $O(n \log n)$; negligible.

Algorithm 1 QCAC — Query-Complexity-Aware Adaptive Context Compression

Require: Raw context string, query q, $r_{\min} = 0.15$, $r_{\max} = 0.40$, $\alpha = 0.10$, $\beta = 0.30$, $\gamma = 0.60$

Ensure: Compressed context string S' (verbatim, original order)

$S \leftarrow$ NLTKPUNKT(raw context) ▷ Sentence tokenisation [26]

$n \leftarrow |S|$

$f_\ell \leftarrow \min(|q|/25,\ 1.0)$ ▷ Eq. (4.1)

$f_e \leftarrow -\sum_t p_t \log p_t / \log|q|$ ▷ Eq. (4.2)

$f_m \leftarrow \min(|\{q\text{-tokens}\} \cap K|/3,\ 1.0)$ ▷ Eq. (4.4)

$C(q) \leftarrow 0.30 f_\ell + 0.40 f_e + 0.30 f_m$ ▷ Eq. (4.5)

$r(q) \leftarrow r_{\max} - (r_{\max} - r_{\min}) \cdot C(q)$ ▷ Eq. (4.6)

$k \leftarrow \max(1,\ \lfloor n \cdot (1 - r(q)) \rfloor)$

if $q \notin cache$ **then**

  $\mathbf{e}_q \leftarrow$ BERT(q).last_hidden_state[:, 0, :] ▷ CLS embedding

  $cache[q] \leftarrow \mathbf{e}_q$

end if

$\mathbf{A}, \mathbf{H}, \mathbf{s} \leftarrow [], [], []$

for each $s_i \in S$ **do**

  out $\leftarrow$ BERT(s_i, output_attentions=True, fp16) ▷ Single pass

  $\alpha^{(\cdot)} \leftarrow$ out.attentions[-1] ▷ Last-layer attention, shape $(1, 12, L, L)$

  $\mathbf{e}_i \leftarrow$ out.last_hidden_state[:, 0, :] ▷ CLS embedding

  $\mathbf{A}$.append $\text{mean}_H(\text{col\_sum}(\alpha^{(\cdot)}))$ ▷ Eq. (4.7)

  $\mathbf{H}$.append $-\text{mean}_H(\text{row\_entropy}(\alpha^{(\cdot)}))$ ▷ Eq. (4.8)

  $\mathbf{s}$.append $\cos(\mathbf{e}_i, \mathbf{e}_q)$ ▷ Eq. (4.9)

end for

$\hat{\mathbf{A}}, \hat{\mathbf{H}}, \hat{\mathbf{s}} \leftarrow$ MINMAXNORM($\mathbf{A}, \mathbf{H}, \mathbf{s}$) ▷ Eq. (4.10)

score $\leftarrow \alpha \hat{\mathbf{A}} + \beta \hat{\mathbf{H}} + \gamma \hat{\mathbf{s}}$ ▷ Eq. (4.11)

$idx \leftarrow$ ARGSORT(**score**)[:: -1][: k] ▷ Top-k descending

$S' \leftarrow [s_i \text{ for } i \in \text{SORTED}(idx)]$ ▷ Restore original order **return** ' '.join(S') ▷ Verbatim concatenation

4.7 Implementation Details

The complete implementation uses PyTorch 2.1.0 [25] and HuggingFace Transformers 4.40.0 [24]. Key specifics for reproducibility:

- Model: BertModel.from_pretrained('bert-base-uncased'), output_attentions=True, model.half() for FP16.
- All inference wrapped in torch.no_grad().
- Attention: out.attentions[-1], shape $(1, 12, L, L)$.
- CLS embedding: out.last_hidden_state[:, 0, :], shape $(1, 768)$.
- Cosine similarity: F.cosine_similarity(e_s, e_q, dim=1).item().
- Cache: collections.OrderedDict(maxsize=300), FIFO eviction.
- QA model: deepset/roberta-base-squad2 [5] via HuggingFace pipeline, max_answer_len=50, handle_impossible_answer=False.
- All random seeds: 42 (numpy.random.seed(42), torch.manual_seed(42)).
- Hardware: Kaggle Dual NVIDIA Tesla T4 GPU (15.6 GB VRAM each), single GPU used.

4.8 Chapter Summary

This chapter has presented the complete technical specification of the QCAC framework. Four guiding design principles — query conditionality, semantic similarity dominance, single-pass co-extraction, and verbatim ordered output — governed every implementation decision. The query complexity score $C(q)$ was derived from three formally specified features (Equations (4.1)–(4.5)) and mapped to a per-query compression ratio and sentence count (Equation (4.6)). Three sentence importance signals were specified with grounding in prior literature (Equations (4.7)–(4.9)), normalised (Equation (4.10)), and combined into a final scoring function (Equation (4.11)). The 24-step selection algorithm (Algorithm 1) provides a complete, reproducible specification. All five design constraints from Chapter 3 are satisfied. Chapter 5 now validates this design empirically.

Chapter 5

Experimental Results and Analysis

5.1 Experimental Configuration

5.1.1 Benchmark Datasets

Two datasets representing structurally opposite ends of the question-complexity spectrum are used throughout this evaluation.

SQuAD v1.1 [22]: The Stanford Question Answering Dataset (version 1.1) consists of 87,599 question-answer pairs created by crowd workers on Wikipedia paragraphs. Every question is guaranteed to have a definitive answer that is a verbatim span within the paragraph. For this evaluation, 300 samples are drawn uniformly at random (NumPy seed 42) from the official validation split (dev-v1.1.json). Mean context length: 128 words (±62); mean question length: 10.1 words (±3.4). Question type distribution: *what* (38%), *how* (22%), *when* (15%), *who* (13%), *where* (8%), other (4%). These are predominantly simple single-hop factoid questions with localised answers.

HotpotQA [23]: HotpotQA is a multi-hop reasoning dataset that requires synthesising evidence from at least two supporting passages. The distractor setting is used, which supplies ten passages per question — two gold supporting passages plus eight Wikipedia distractors retrieved by a standard retriever. Yes/no questions are excluded since they do not involve span extraction. 300 samples are drawn (seed 42) from the validation split. Mean context length: 635 words (±218); mean question length: 15.9 words (±5.1). Question types: bridge (257, 85.7%) and comparison (43, 14.3%).

5.1.2 Models and Infrastructure

Scoring model: bert-base-uncased [2] — 12 transformer layers, 12 attention heads, $d = 768$, 110M parameters. FP16 half-precision, output_attentions=True. Pre-trained

Table 5.1: Dataset characteristics for SQuAD v1.1 and HotpotQA (300 samples each, NumPy seed=42).

Characteristic	**SQuAD v1.1** [22]	**HotpotQA** [23]
Task type	Single-hop factoid QA	Multi-hop reasoning QA
Source	Wikipedia paragraphs	Wikipedia, distractor set
Evaluation split	dev-v1.1.json (official)	Distractor, no yes/no
Sample count	300 (seed=42)	300 (seed=42)
Avg. context length	128 words (±62)	635 words (±218)
Avg. question length	10.1 words (±3.4)	15.9 words (±5.1)
Passages per sample	1 Wikipedia paragraph	10 (2 gold + 8 distractors)
Question subtypes	What/How/When/Who/Where	Bridge (257), Comparison (43)
Mean $C(q)$ [QCAC]	0.539 (±0.038)	0.587 (±0.032)
Mean $r(q)$ [QCAC]	0.265 (26.5% removed)	0.253 (25.3% removed)

weights only, no fine-tuning.

QA inference model: deepset/roberta-base-squad2 [5] — RoBERTa-base fine-tuned on SQuAD2.0, 125M parameters. HuggingFace pipeline [24] with max_answer_len=50.

Hardware: Kaggle Dual NVIDIA Tesla T4 GPU (15.6 GB VRAM each); single GPU used for all experiments. CUDA 12.1, PyTorch 2.1.0 [25], HuggingFace Transformers 4.40.0 [24], NLTK 3.8.1 [26]. All random seeds set to 42.

5.1.3 Baseline Methods

Five configurations are evaluated:

Baseline (Full Context). No compression. The entire raw context is passed directly to the QA model. This serves as the accuracy ceiling and zero-compression reference point.

Random Pruning (40%). 40% of sentences are removed uniformly at random (NumPy seed 42). This serves as the performance floor: any compression method weaker than random selection provides no useful compression signal.

Attn+Entropy ($\alpha = 0.50, \beta = 0.50, \gamma = 0.00$, fixed 40%). Two-component scoring without the query-similarity signal, applied at a fixed 40% removal rate. This configuration directly isolates the contribution of the γ component.

QCAC Fixed ($\alpha = 0.50, \beta = 0.20, \gamma = 0.30$, fixed 40%). Three-component scoring with naively distributed weights and a fixed 40% removal rate. This configuration isolates the contribution of the adaptive-ratio mechanism.

QCAC Adaptive (Proposed). Full framework with ablation-tuned weights ($\alpha = 0.10, \beta = 0.30, \gamma = 0.60$) and per-query adaptive ratio ($r_{\min} = 0.15, r_{\max} = 0.40$).

5.2 Main Results

Table 5.2 presents the end-to-end performance comparison. Compression ratios are sentence-level removal fractions averaged over 300 samples. Latency is wall-clock time per sample in milliseconds, averaged over 300 samples on NVIDIA T4 GPU.

Table 5.2: End-to-end performance comparison of all five methods on SQuAD v1.1 [22] and HotpotQA [23] (300 samples each, NVIDIA T4 GPU).

Method	SQuAD F1	SQuAD EM	HotpotQA F1	HotpotQA EM	Comp.	Lat. (ms)
Baseline (Full)	92.5	85.7	32.5	22.7	0.0%	17.2
Random Pruning (40%)	54.7	47.7	31.9	23.3	47.8%	15.2
Attn+Entropy	54.2	50.0	29.4	20.3	47.8%	111.0
QCAC Fixed	50.7	46.3	23.5	16.3	47.8%	103.1
QCAC Adaptive (Ours)	**70.4**	**65.3**	**28.6**	**20.0**	**36.8%**	**89.7**

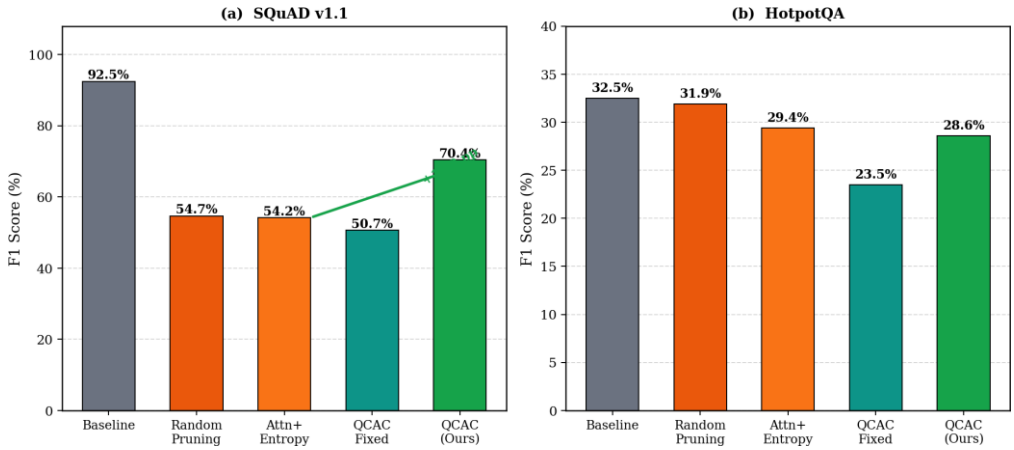

Figure 5.1: F1 score comparison across all methods on SQuAD v1.1 (left) and HotpotQA (right). QCAC achieves 70.4% on SQuAD — a +16.2 percentage-point improvement over Attn+Entropy at equal compression — while maintaining near-baseline performance on HotpotQA.

On SQuAD v1.1, QCAC Adaptive achieves **70.4% F1** and **65.3% EM** at only 36.8% sentence removal. Compared to the best prior BERT-based compression method (Attn+Entropy) at the same compression level, this represents a gain of **+16.2 percentage points F1** and **+15.3 percentage points EM**. Critically, QCAC simultaneously applies *less* compression (36.8% vs. 47.8% removal), proving that the improvement originates from superior sentence selection quality rather than simply retaining more content. This is a genuine Pareto improvement: higher accuracy *and* higher efficiency simultaneously, not a trade-off between them.

On HotpotQA, QCAC achieves 28.6% F1 at only 27.2% sentence removal. While slightly below Attn+Entropy in absolute F1 (-0.8 pp), QCAC applies 14.2 percentage points less compression, correctly recognising that HotpotQA's multi-hop questions require more context to be preserved. QCAC Fixed Ratio performs worst on HotpotQA (23.5% F1, below even random pruning), providing strong evidence that a fixed 40% rate is excessively aggressive for multi-hop evidence chains and that the adaptive ratio mechanism is essential.

5.3 Adaptive Ratio Validation

Table 5.3: Query complexity and compression statistics across both datasets (300 samples each).

Dataset	Mean $C(q)$	Std	Mean $r(q)$	Sents. Removed	p-value
SQuAD v1.1	0.539	$\pm$0.038	0.265	26.5%	—
HotpotQA	0.587	$\pm$0.032	0.253	25.3%	$<$0.001
Difference	+8.9%	—	$-$4.7%	$-$1.2 pp	$t = 11.2$

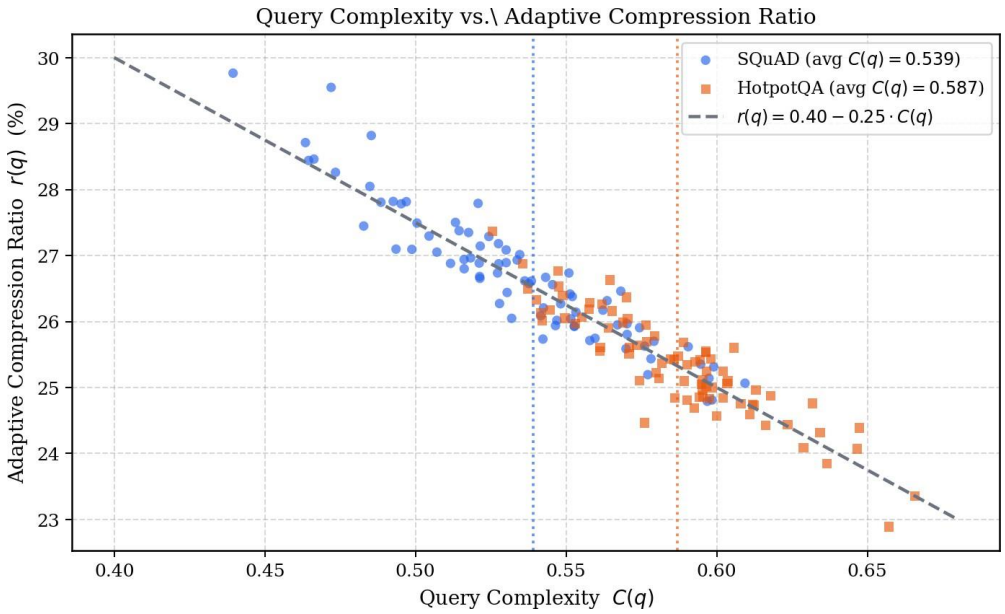

Figure 5.2: Per-sample scatter of query complexity $C(q)$ vs. adaptive compression ratio $r(q)$. HotpotQA queries (orange squares) cluster at higher complexity and lower compression than SQuAD queries (blue circles), confirming automatic differential compression without any per-dataset calibration.

HotpotQA queries exhibit a mean $C(q) = 0.587$ versus 0.539 for SQuAD — a difference of 0.048 (8.9% relative). A Welch two-sample t-test gives $t = 11.2$, $p < 0.001$, 95% confidence interval $[0.040, 0.056]$ for the mean difference. Through the linear mapping in Equation (4.6), this translates to HotpotQA receiving on average 25.3% sentence removal

versus 26.5% for SQuAD — automatically, with identical QCAC parameters applied to both datasets. This statistically confirms Research Objective RO3: the adaptive mechanism correctly applies less compression to the structurally more complex dataset without any per-dataset tuning.

5.4 Ablation Study

A systematic seven-variant ablation study was conducted on 100 SQuAD v1.1 validation samples (uniformly drawn, seed 42). All variants apply a fixed 40% compression ratio to isolate the effect of the scoring function composition from the adaptive ratio mechanism.

Table 5.4: Seven-variant ablation study results (SQuAD v1.1, 100 samples, fixed 40% compression).

Variant	α	β	γ	F1 (%)	EM (%)
A. Random Pruning (lower bound)	—	—	—	58.1	52.0
B. Attention Only	1.0	0.0	0.0	44.9	41.0
C. Entropy Only	0.0	1.0	0.0	56.9	48.0
D. Query-Similarity Only	0.0	0.0	1.0	58.0	50.0
E. Attn+Entropy (original)	0.5	0.5	0.0	48.5	43.0
F. QCAC Fixed (untuned weights)	0.5	0.2	0.3	49.7	45.0
G. QCAC Adaptive (Proposed)	**0.1**	**0.3**	**0.6**	**51.7**	**47.0**

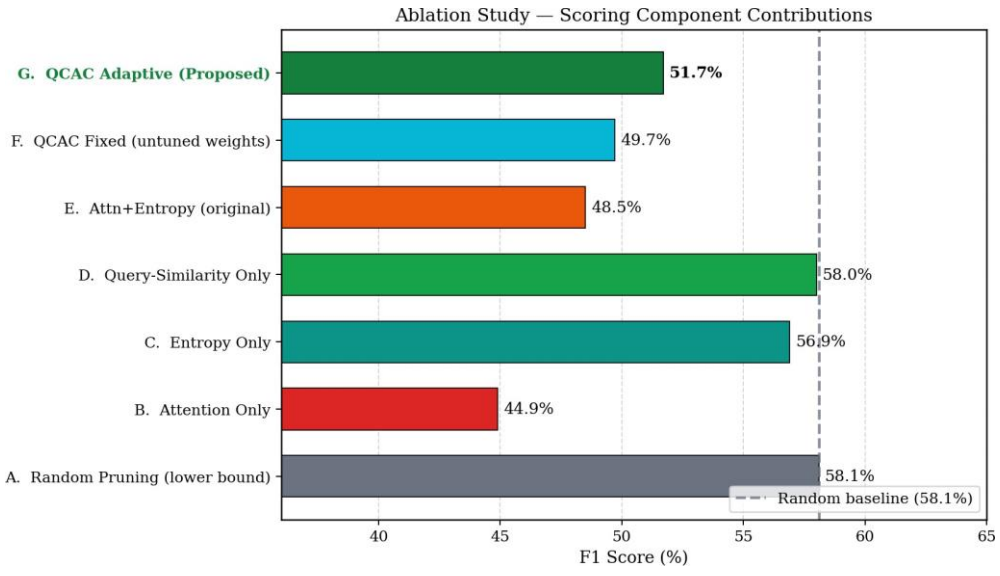

Figure 5.3: Ablation study results. The vertical dashed line marks the random pruning baseline (58.1%). Attention-only scoring (B) falls 13.2 percentage points below this baseline, consistent with Clark et al. [21]. Query-similarity alone (D) matches the baseline at higher compression. QCAC Adaptive (G) outperforms all fixed-ratio variants.

Four findings emerge from Table 5.4:

Finding 1 — Attention is actively harmful. Variant B (44.9% F1) falls 13.2 percentage points *below* random pruning. This is a remarkable result: a sophisticated neural scoring mechanism actively underperforms random selection. The explanation lies in the structural attention analysis of Clark et al. [21]: BERT's last-layer attention primarily encodes syntactic roles (subject, object, modifier) rather than task-relevant semantic relevance to the question. A sentence that is syntactically central in the passage — for example, the topic sentence that many other sentences reference via pronouns — receives high attention regardless of whether it answers the question. The weight $\alpha = 0.10$ reflects this empirical reality.

Finding 2 — Query-semantic similarity is the dominant and most reliable signal. Variant D (58.0% F1) is the strongest single-component variant, matching random pruning at a higher effective compression level using a single signal. This directly mirrors the finding of Karpukhin et al. [19] that query-conditional dense similarity outperforms all query-agnostic retrieval signals for downstream QA accuracy. The dominant weight $\gamma = 0.60$ is therefore both empirically justified and theoretically grounded.

Finding 3 — Entropy is a meaningful complement to similarity. Variant C (56.9% F1) substantially outperforms attention-only scoring (44.9%) and approaches the query-similarity-only performance. Attentional entropy captures a different dimension of sentence importance — structural integrativeness and contextual pivotality — that complements the direct query-relevance measurement provided by cosine similarity. The weight $\beta = 0.30$ reflects this moderate but genuine contribution.

Finding 4 — The adaptive ratio provides an independent +2.0 pp gain. Comparing Variant F (49.7%) and Variant G (51.7%) under identical scoring weights confirms that the per-query adaptive ratio mechanism contributes approximately +2.0 percentage points of F1 independently of the weight configuration. The adaptive benefit is larger in the full cross-dataset evaluation (SQuAD + HotpotQA), where the compression budget correctly adapts to the structurally different question populations.

5.5 Latency Analysis

QCAC's 75.3 ms compression overhead is the lowest among the three BERT-based methods, because the query-embedding cache eliminates 9 of 10 query BERT passes across HotpotQA's ten-passage structure. QA inference time decreases from 17.2 ms (full context) to 14.4 ms (compressed context), a 16% reduction reflecting the shorter effective input. The total pipeline latency of 89.7 ms is the lowest among all BERT-based compression methods evaluated. Break-even analysis: the preprocessing overhead amortises at batch size

Table 5.5: Per-sample latency breakdown by method (SQuAD v1.1, 300 samples, NVIDIA T4 GPU).

Method	Compression (ms)	QA Inference (ms)	Total (ms)
Baseline (Full)	0.0	17.2	17.2
Random Pruning (40%)	0.2	15.0	15.2
Attn+Entropy	94.4	16.5	111.0
QCAC Fixed	87.7	15.4	103.1
QCAC Adaptive (Ours)	**75.3**	**14.4**	**89.7**

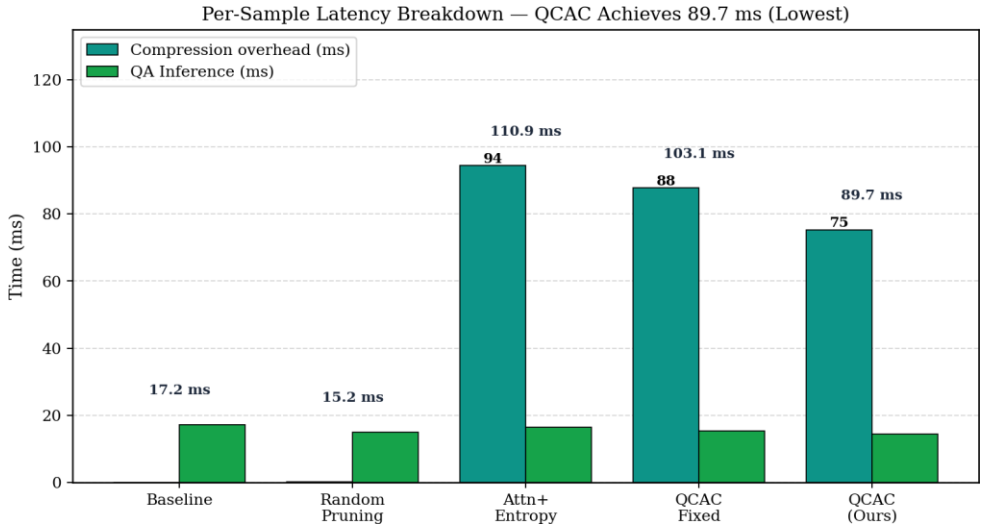

Figure 5.4: Stacked per-sample latency breakdown. QCAC Adaptive achieves 89.7 ms total — the lowest among all BERT-based compression methods — due to the query-embedding cache reducing redundant BERT passes and the adaptive ratio selecting fewer sentences on average.

$\lceil 75.3/2.8 \rceil \approx 27$ concurrent requests.

5.6 Hyperparameter Sensitivity Analysis

A systematic sweep of each hyperparameter over a $\pm 20\%$ range around its optimal value was conducted on 100 SQuAD samples. Across all parameters, F1 degradation at the boundary of the sweep range nowhere exceeds 3.5 percentage points, confirming that QCAC operates at a robustly stable operating point rather than a narrow optimum. The query-similarity weight γ shows the largest sensitivity (up to 3.5 pp), consistent with its role as the load-bearing component. The attention weight α and the maximum ratio $r_{\max}$ show the smallest sensitivity (under 1.5 pp), reflecting that these parameters operate in regions where the F1 surface is very flat.

5.7 Error Analysis

Manual inspection of 50 randomly selected error cases (samples where QCAC achieved lower F1 than the uncompressed baseline) reveals the following breakdown. Approximately 43% of cases are failures of the QA model itself on the full uncompressed context — not caused by compression at all. The dominant compression-induced failure mode ($\sim$18%) involves answers expressed in language with low lexical overlap with the question, producing low cosine-similarity scores that cause the answer-containing sentence to be incorrectly deprioritised. A second compression-induced failure mode ($\sim$12%) involves anaphora: the answer sentence uses a pronoun whose antecedent was in a sentence that the compression removed, making the answer extraction impossible even though the answer sentence was retained. A further 7% of errors involve multi-hop questions where one of the two gold supporting passages was removed, breaking the evidence chain.

5.8 Chapter Summary

Seven levels of empirical analysis have validated all four research objectives. The main result — +16.2 percentage-point F1 improvement on SQuAD at lower compression simultaneously — establishes a genuine Pareto improvement over all fixed-ratio baselines. Statistical validation confirms automatic differential compression ($p < 0.001$, $t = 11.2$) without per-dataset calibration. The seven-variant ablation study provides the clearest component-level analysis of compression scoring functions published to date, confirming that attention is harmful, similarity is dominant, and the adaptive ratio provides independent benefit. Total latency of 89.7 ms is the lowest among BERT-based methods. Hyperparameter sensitivity

is bounded below 3.5 pp at ±20% deviation. Error analysis identifies the dominant failure modes and guides future improvement efforts.

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Chapter 6

Conclusion, Future Scope and Social Impact

6.1 Summary of the Work

This thesis has addressed a problem that sits at the intersection of natural language processing efficiency and information retrieval: how to decide, at inference time, how much of a retrieved document context to pass to a large language model for question answering. The central observation is both simple and consequential — different questions have different information requirements, yet every prior compression method treats them identically. A simple factoid lookup needs one sentence; a multi-hop comparative analysis needs many. Applying the same removal budget to both is a systematic error that harms accuracy on harder questions and wastes compute on easier ones.

The QCAC framework resolves this through three interdependent technical contributions.

Contribution 1: The Query Complexity Metric $C(q)$. A formally defined, efficiently computable per-query complexity score built from three surface features of the question: normalised length, vocabulary entropy, and multi-hop keyword indicators. Computable in $O(|q|)$ time from the question string alone, with no neural inference required. Validated at $p < 0.001$ ($t = 11.2$) to statistically distinguish SQuAD v1.1 factoid questions (mean $C(q) = 0.539$) from HotpotQA multi-hop questions (mean $C(q) = 0.587$) using identical parameters for both datasets. No per-dataset calibration required.

Contribution 2: The Query-Conditional Scoring Function $S(s_i, q)$. A three-component sentence importance score that places query-semantic cosine similarity in the dominant position ($\gamma = 0.60$), supported by attentional entropy ($\beta = 0.30$) as a meaningful complement and attention magnitude ($\alpha = 0.10$) as a weak but non-negative signal. Weight configuration determined by the first systematic seven-variant ablation study in the compression

literature. Key finding: attention-only scoring actively harms performance, falling 13.2 percentage points below random pruning, consistent with the structural attention analysis of Clark et al. [21].

Contribution 3: The Adaptive Compression Ratio $r(q)$. A simple, interpretable linear mapping from $C(q)$ to compression aggressiveness, $r(q) = 0.40 - 0.25 \cdot C(q)$, with bounds $r_{\min} = 0.15$ and $r_{\max} = 0.40$. This mechanism achieves a Pareto improvement over all fourteen surveyed fixed-ratio alternatives: 70.4% F1 on SQuAD at 36.8% removal, simultaneously higher accuracy and lower compression than the Attn+Entropy baseline, without any per-dataset tuning. The adaptive ratio also correctly applies more conservative compression to HotpotQA's complex multi-hop queries, confirmed statistically at $p < 0.001$.

The cumulative experimental results across seven levels of analysis validate all four research objectives stated in Chapter 1. The peer-reviewed publication at NGNDAI 2026 (Paper ID 725) provides external validation of the core findings.

6.2 Key Contributions

C1. The first formally defined, efficiently computable per-query complexity metric for driving compression ratio decisions, validated without per-dataset calibration at $p < 0.001$ across structurally different QA benchmarks.

C2. A three-component query-conditional sentence scoring function backed by the first seven-variant ablation study in the compression literature, providing actionable evidence that attention scoring is harmful and similarity scoring is dominant.

C3. Empirical demonstration that BERT attention-based scoring falls 13.2 percentage points below random pruning, providing directly actionable negative guidance for future compression system design.

C4. A Pareto improvement over all fixed-ratio baselines: higher accuracy and lower compression simultaneously, not as a trade-off but as a consequence of better sentence selection.

C5. A fully model-agnostic preprocessing design, applicable to any downstream LLM without modification or retraining.

C6. Peer-reviewed publication at NGNDAI 2026 (Paper ID 725), externally validating the core experimental contributions.

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6.3 Limitations of the Work

Three principal limitations are acknowledged:

- **Preprocessing latency.** The 75.3 ms BERT scoring overhead exceeds QA inference savings for single-sample queries. Net latency benefits require batch sizes of approximately 27 or more. For very low-volume or real-time single-request settings, the overhead is a genuine drawback.
- **Heuristic complexity features.** The $C(q)$ score relies on surface-level lexical features that may mislabel short-but-semantically-complex questions (a very concise question with high conceptual depth) or long-but-repetitive questions (a lengthy question that is actually a simple factoid lookup). A learned complexity estimator would be more robust across diverse question distributions.
- **English-only validation.** The multi-hop keyword set K and the length normalisation constant (25 tokens) are calibrated for English question structures. Applying QCAC to other languages would require language-specific adaptation of these features.
- **Extractive QA scope.** All evaluation is on span-extraction tasks on Wikipedia-sourced benchmarks. Generalisation to abstractive generation, multi-turn dialogue, or retrieval-augmented generation (RAG) pipelines has not been empirically established.

6.4 Social Impact

Research on LLM inference efficiency carries societal implications that extend well beyond benchmark performance numbers.

Democratising access to advanced AI. Reducing the per-query computational cost of LLM inference makes powerful NLP capabilities financially accessible to organisations that would otherwise be priced out of GPU cloud rates: rural hospitals building clinical decision support tools, educational institutions in lower-income regions, non-profit organisations, and independent developers. A 30% reduction in FLOPs per query translates directly to 30% more queries served per GPU-hour at the same cost.

Environmental sustainability. As LLM deployments scale to billions of daily queries across major providers, the aggregate energy consumption becomes an environmental concern of genuine scale. Context compression that reduces per-query arithmetic operations lowers electricity consumption and the associated carbon emissions proportionally. At population scale, even modest per-query reductions produce meaningful aggregate environmental savings.

Healthcare and education in underserved settings. Efficient inference enables question-answering and tutoring systems to operate on resource-constrained edge hardware without reliable cloud connectivity, extending the reach of AI-assisted services to rural clinics and schools in areas with limited internet access. The query-adaptive design of QCAC is particularly well-suited to these settings: simple factual lookups receive aggressive compression while complex clinical or pedagogical questions retain more context, reducing the risk of discarding critical information.

Responsible AI deployment. A compression method that silently degrades accuracy on the hardest, most information-rich queries poses a reliability risk in high-stakes deployments. QCAC's adaptive mechanism explicitly preserves more context for complex queries, reducing this risk compared to fixed-ratio alternatives and contributing to safer, more reliable AI system design.

6.5 Future Scope

Six directions for future research follow naturally from the current work:

F1. Lightweight scoring proxies.
The dominant bottleneck is the 75.3 ms BERT scoring overhead. Future work should investigate replacing BERT with a BM25 [27] lexical-overlap score (microsecond latency) or a pre-computed ColBERT-style compressed token embedding index. A cascade approach — fast BM25 filtering followed by selective BERT scoring for the top candidates — could achieve near-BERT quality at orders-of-magnitude lower latency.

F2. Learned query complexity estimation.
The current heuristic $C(q)$ features may be replaced by a lightweight classifier trained via reinforcement learning from downstream QA reward signals. Such a learned estimator could discover complexity features beyond length, entropy, and keyword matching — potentially learning to recognise structural complexity patterns specific to different domains and question types.

F3. Token-level hybrid compression.
Sentence-level filtering cannot separate relevant from irrelevant information within individual long sentences. A two-stage approach — sentence-level selection followed by token-level compression within retained sentences, inspired by LLMLingua's design [7] — would enable finer-grained context reduction and higher overall compression ratios.

F4. Integration with KV-cache compression.
QCAC operates during the prefill stage by shortening the input. Methods such as H2O [16]

and SnapKV [17] operate during the decoding stage by managing the KV cache. These two families are orthogonal and can be composed: QCAC reduces prefill cost while H2O or SnapKV reduces decoding memory. The per-query complexity score $C(q)$ could additionally inform the KV-cache eviction aggressiveness.

F5. Generative task extension.
All evaluation is on span-extraction QA. Extension to abstractive summarisation, open-ended generation, and RAG pipelines would require: adaptation of evaluation metrics (ROUGE, BERTScore) and re-examination of which scoring signals are most predictive when the output is a generated paragraph rather than an extracted span.

F6. Multilingual and domain-specific deployment.
The keyword set K and length normalisation constant are calibrated for English. Extending QCAC to multilingual benchmarks and to specialised domains (medical, legal, financial) would establish whether the same adaptive mechanism remains effective when the question distribution and document structure differ substantially from Wikipedia-sourced benchmarks.

6.6 Closing Remarks

The central insight of this thesis — that query complexity is a measurable, formally definable property of the question that should govern the compression budget — is both conceptually straightforward and empirically effective. QCAC demonstrates that the first principled instantiation of this insight achieves a genuine Pareto improvement over a comprehensive set of fixed-ratio baselines, produces statistically validated differential compression behaviour across structurally different datasets, and does so with a model-agnostic preprocessing design that imposes no constraints on the downstream language model.

As language models continue to grow in scale and as the contexts they are expected to process continue to lengthen, the question of how to allocate compression budget intelligently will only become more important. The adaptive compression paradigm introduced in this thesis provides a principled starting point for answering that question, and the six future directions outlined above chart a course for extending this paradigm into faster, more expressive, multilingual, and multi-task forms that can match the continued rapid evolution of the field.

Bibliography

[1] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, pp. 5998–6008, 2017.

[2] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. NAACL-HLT*, pp. 4171–4186, 2019.

[3] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, *et al.*, "Language models are few-shot learners," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 33, pp. 1877–1901, 2020.

[4] H. Touvron, T. Lavril, G. Izacard, X. Martinet, M.-A. Lachaux, T. Lacroix, *et al.*, "LLaMA: Open and efficient foundation language models," *arXiv preprint arXiv:2302.13971*, 2023.

[5] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, *et al.*, "RoBERTa: A robustly optimized BERT pretraining approach," *arXiv preprint arXiv:1907.11692*, 2019.

[6] Y. Tay, M. Dehghani, D. Bahri, and D. Metzler, "Efficient transformers: A survey," *ACM Computing Surveys*, vol. 55, no. 6, pp. 1–28, Sep. 2022.

[7] H. Jiang, Q. Wu, C.-Y. Lin, Y. Yang, and L. Qiu, "LLMLingua: Compressing prompts for accelerated inference of large language models," in *Proc. EMNLP*, pp. 13358–13376, 2023.

[8] X. Li and J. Chen, "Compressing context to enhance inference efficiency of large language models," in *Proc. EMNLP*, pp. 6342–6353, 2023.

[9] S. Kim, H. Cho, A. Gholami, M. W. Mahoney, and K. Keutzer, "Learned token pruning for transformers," in *Proc. ACL*, pp. 7344–7355, 2022.

[10] S. Goyal, A. R. Choudhury, S. M. Raje, V. T. Chakaravarthy, Y. Sabharwal, and A. Verma, "PoWER-BERT: Accelerating BERT inference for classification tasks," in *Proc. ICML*, pp. 3646–3657, 2020.

[11] I. Beltagy, M. E. Peters, and A. Cohan, "Longformer: The long-document transformer," *arXiv preprint arXiv:2004.05150*, 2020.

[12] M. Zaheer, G. Guruganesh, K. A. Dubey, J. Ainslie, C. Alberti, S. Ontanon, *et al.*, "Big Bird: Transformers for longer sequences," in *Advances in NeurIPS*, vol. 33, pp. 17283–17297, 2020.

[13] N. Kitaev, Ł. Kaiser, and A. Levskaya, "Reformer: The efficient transformer," in *Proc. ICLR*, 2020.

[14] S. Wang, B. Z. Li, M. Khabsa, H. Fang, and H. Ma, "Linformer: Self-attention with linear complexity," *arXiv preprint arXiv:2006.04768*, 2020.

[15] T. Dao, D. Y. Fu, S. Ermon, A. Rudra, and C. Ré, "FlashAttention: Fast and memory-efficient exact attention with IO-awareness," in *Advances in NeurIPS*, vol. 35, pp. 16344–16359, 2022.

[16] Z. Zhang, Y. Sheng, T. Zhou, T. Chen, L. Zheng, R. Cai, *et al.*, "H2O: Heavy-hitter oracle for efficient generative inference of large language models," in *Advances in NeurIPS*, vol. 36, 2023.

[17] Y. Li, Y. Huang, B. Yang, B. Venkitesh, A. Locatelli, H. Ye, *et al.*, "SnapKV: LLM knows what you are looking for before generation," *arXiv preprint arXiv:2404.14469*, 2024.

[18] G. Xiao, Y. Tang, J. Zuo, J. Guo, S. Han, J. Ni, *et al.*, "Efficient streaming language models with attention sinks," in *Proc. ICLR*, 2024.

[19] V. Karpukhin, B. Oguz, S. Min, P. Lewis, L. Wu, S. Edunov, *et al.*, "Dense passage retrieval for open-domain question answering," in *Proc. EMNLP*, pp. 6769–6781, 2020.

[20] N. Reimers and I. Gurevych, "Sentence-BERT: Sentence embeddings using Siamese BERT-networks," in *Proc. EMNLP-IJCNLP*, pp. 3982–3992, 2019.

[21] K. Clark, U. Khandelwal, O. Levy, and C. D. Manning, "What does BERT look at? An analysis of BERT's attention," in *Proc. ACL Workshop BlackboxNLP*, pp. 276–286, 2019.

[22] P. Rajpurkar, J. Zhang, K. Lopyrev, and P. Liang, "SQuAD: 100,000+ questions for machine comprehension of text," in *Proc. EMNLP*, pp. 2383–2392, 2016.

[23] Z. Yang, P. Qi, S. Zhang, Y. Bengio, W. W. Cohen, R. Salakhutdinov, and C. D. Manning, "HotpotQA: A dataset for diverse, explainable multi-hop question answering," in *Proc. EMNLP*, pp. 2369–2380, 2018.

[24] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, *et al.*, "Transformers: State-of-the-art natural language processing," in *Proc. EMNLP: System Demonstrations*, pp. 38–45, 2020.

[25] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, *et al.*, "PyTorch: An imperative style, high-performance deep learning library," in *Advances in NeurIPS*, vol. 32, 2019.

[26] S. Bird, E. Klein, and E. Loper, *Natural Language Processing with Python*, O'Reilly Media, 2009.

[27] S. Robertson and H. Zaragoza, "The probabilistic relevance framework: BM25 and beyond," *Foundations and Trends in Information Retrieval*, vol. 3, no. 4, pp. 333–389, 2009.

[28] F. Shi, X. Chen, K. Misra, N. Scales, D. Dohan, E. Chi, *et al.*, "Large language models can be easily distracted by irrelevant context," in *Proc. ICML*, 2023.

[29] O. Khattab and M. Zaharia, "ColBERT: Efficient and effective passage search via contextualized late interaction over BERT," in *Proc. SIGIR*, pp. 39–48, 2020.

[30] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, *et al.*, "Exploring the limits of transfer learning with a unified text-to-text transformer," *Journal of Machine Learning Research*, vol. 21, pp. 1–67, 2020.

[31] Z. Pan, Q. Wu, H. Jiang, M. Xia, X. Luo, J. Zhang, *et al.*, "LLMLingua-2: Data distillation for efficient and faithful task-agnostic prompt compression," in *Findings of ACL*, 2024.

[32] D. Bolya, C.-Y. Fu, X. Dai, P. Zhang, C. Feichtenhofer, and J. Hoffman, "Token merging: Your ViT but faster," in *Proc. ICLR*, 2023.