

# Contextual Graph Transformer: A Small Language Model for Enhanced Technical Document Answering

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**Abstract**—Standard transformer-based language models, while powerful for general text, often struggle with the fine-grained syntax and entity relationships in complex technical documents. To address this, we propose the Contextual Graph Transformer (CGT), a hybrid neural architecture that combines Graph Neural Networks (GNNs) and Transformers for domain-specific question answering. CGT constructs a dynamic graph over input tokens using sequential, skip-gram, and semantic similarity edges, which is processed by GATv2Conv layers for local structure learning. These enriched embeddings are then passed to a Transformer encoder to capture global dependencies.

Unlike generic large models, technical domains often require specialized language models with stronger contextualization and structure awareness. CGT offers a parameter-efficient solution for such use cases. Integrated into a Retrieval-Augmented Generation (RAG) pipeline, CGT outperforms baselines like GPT-2 and BERT, achieving 24.7% higher accuracy than GPT-2 with 62.4% fewer parameters. This gain stems from CGT’s ability to jointly model structural token interactions and long-range semantic coherence. The model is trained from scratch using a two-phase approach: pretraining on general text followed by fine-tuning on domain-specific manuals. This highlights CGT’s adaptability to technical language, enabling better grounding, entity tracking, and retrieval-augmented responses in real-world applications.

**Index Terms**—Contextual Graph Transformer, Small Language Models, Domain-Specific NLP, Graph Neural Networks, Transformers, Retrieval-Augmented Generation, Technical Question Answering, Parameter Efficiency.

## I. INTRODUCTION

The rapid advancement of natural language processing has produced powerful language models for general text understanding. However, technical documents pose unique challenges due to their complex structure, specialized terminology, and intricate entity relationships. Traditional transformer-based models often struggle to capture the fine-grained syntax and local dependencies essential for accurately interpreting such content. This necessitates domain-adaptive architectures capable of modeling structural and contextual nuances effectively.

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The limitations of current approaches become particularly evident when dealing with industrial technical documents, which frequently combine textual descriptions with structured data such as tables, specifications, and hierarchical information. These documents require models that can simultaneously process sequential text and understand the local relationships between technical terms, product specifications.

### A. Motivation and Problem Statement

Technical document understanding presents several fundamental challenges that existing language models struggle to address effectively:

**Local Relationship Modeling:** Technical documents contain dense clusters of related terms and concepts that require fine-grained understanding of local relationships. For example, in a product specification, the proximity and relationship between a product code, its specifications, and operational parameters are crucial for accurate comprehension.

**Parameter Efficiency:** Large transformer models like GPT-3 and BERT require substantial computational resources, making them impractical for many real-world applications. There is a pressing need for smaller, more efficient models that can achieve comparable or superior performance with significantly fewer parameters.

**Structural Awareness:** Technical documents often contain implicit structural relationships that pure sequential processing may miss. The ability to model these relationships explicitly through graph structures could provide significant advantages.

**Domain Adaptation:** Models must efficiently adapt from general language understanding to specific technical domains without requiring massive amounts of domain-specific training data.

### B. Our Approach

To address these challenges, we propose the Contextual Graph Transformer (CGT), a novel hybrid architecture that combines the local relationship modeling capabilities of Graph Neural Networks with the global context processing strengths of Transformers. Our approach is fundamentally different from existing methods in several key aspects:

- 1) **Dynamic Graph Construction:** We develop a sophisticated algorithm that dynamically constructs graphs from token sequences, capturing both sequential and

semantic relationships through adjacency and skip-gram connections.

- 2) **Hierarchical Processing:** Our model employs a two-stage processing pipeline where GNN layers first extract rich local features, which are then fed into Transformer layers for global context integration.
- 3) **Parameter Efficiency:** With only 46.8M parameters, our model achieves superior performance compared to much larger baselines, demonstrating the effectiveness of hybrid architectural design.
- 4) **Comprehensive Evaluation:** We conduct extensive experiments against multiple established baselines, providing robust empirical validation of our approach.

### C. Contributions

This paper makes the following key contributions:

- Introduction of the Contextual Graph Transformer (CGT), a novel hybrid architecture that effectively combines GNNs and Transformers for technical document understanding
- Development of a dynamic graph construction algorithm that captures local relationships in text through mathematical formulations
- Comprehensive empirical evaluation demonstrating 24.7% performance improvement over GPT-2 with 62.4% fewer parameters
- Integration with RAG systems for practical question-answering applications
- Detailed mathematical analysis of the hybrid architecture’s computational complexity and efficiency

## II. PRIOR ART

### A. Large Language Models and Parameter Efficiency

The field of natural language processing has witnessed remarkable advances with the introduction of large-scale transformer models. BERT [1] demonstrated the power of bidirectional attention mechanisms, while GPT-2 [2] showcased the effectiveness of autoregressive generation. However, these models typically require hundreds of millions or billions of parameters, leading to significant computational overhead.

Recent work has focused on developing more parameter-efficient alternatives. DistilBERT [3] achieved substantial parameter reduction through knowledge distillation, while maintaining reasonable performance. However, these approaches primarily focus on architectural compression rather than fundamental improvements in how local relationships are modeled.

### B. Graph Neural Networks for Natural Language Processing

Graph Neural Networks have emerged as powerful tools for modeling structured relationships in data. The Graph Attention Network (GAT) [4] introduced attention mechanisms to graph processing, enabling more sophisticated relationship modeling. Recent work like GraphCodeBERT [5] has demonstrated the

effectiveness of combining graph structures with transformer architectures for specific domains like code understanding.

However, most existing approaches focus on predetermined graph structures rather than dynamically constructed graphs from text sequences. Our work addresses this limitation by developing algorithms for dynamic graph construction from token sequences.

### C. Hybrid Neural Architectures

The combination of different neural architectures has shown promising results across various domains. Recent work has explored combinations of CNNs and RNNs, as well as attention mechanisms with convolutional layers. However, the systematic combination of GNNs with Transformers for language understanding remains relatively unexplored, particularly for technical document processing.

### D. Technical Document Understanding

Technical document understanding has been addressed through various approaches, including rule-based systems, machine learning methods, and more recently, deep learning approaches. However, most existing methods fail to adequately capture the complex relationships between technical entities and the hierarchical structure inherent in technical documents.

## III. METHODOLOGY

### A. System Architecture Overview

Our SLM-CGT system consists of four main components working in sequence to process technical documents and generate accurate responses. Figure 1 illustrates the complete system architecture.

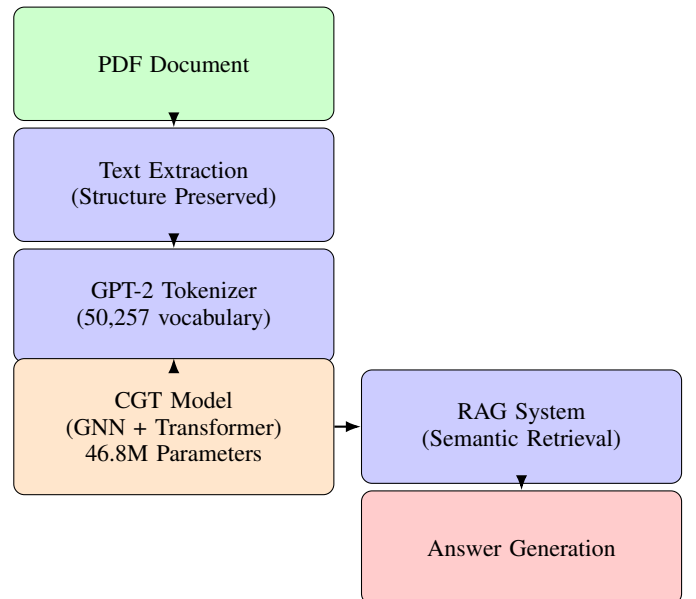


Fig. 1: SLM-CGT System Architecture showing the complete pipeline from PDF document processing to answer generation.

## B. Complete Query Processing Pipeline

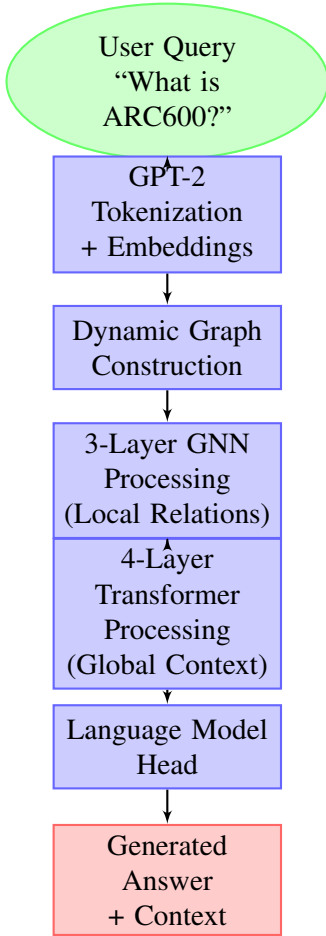


Fig. 2: Complete query processing pipeline through CGT model, showing the flow from user query to generated answer with intermediate representations.

**Mathematical Flow Description:** The graph structure enables meaningful relationship modeling while the Transformer provides global semantic understanding for comprehensive technical document processing through the mathematical transformation  $f : \mathbf{x} \rightarrow \mathbf{y}$  where  $\mathbf{y} = \text{LMHead}(\text{Transformer}(\text{Reshape}(\text{GNN}(\text{GraphConstruct}(\mathbf{x}))))$ .

## C. Problem Formulation

Given an input text sequence  $\mathbf{x} = [x_1, x_2, \dots, x_n]$  representing a technical document or query, our goal is to learn a function  $f : \mathbf{x} \rightarrow \mathbf{y}$  that maps the input to an appropriate output representation for downstream tasks such as question answering. The key challenge is to model both local relationships between nearby tokens and global dependencies across the entire sequence while maintaining parameter efficiency.

Formally, we define the problem as optimizing the joint probability distribution:

$$P(\mathbf{y}|\mathbf{x}) = \prod_{t=1}^T P(y_t|y_{<t}, \mathbf{x}, \mathbf{H}_{\text{CGT}}) \quad (1)$$

$$\mathbf{H}_{\text{CGT}} = \text{Transformer}(\text{GNN}(\text{GraphConstruct}(\mathbf{x}))) \quad (2)$$

$$\log P(\mathbf{y}|\mathbf{x}) = \sum_{t=1}^T \log P(y_t|y_{<t}, \mathbf{H}_{\text{CGT}}) \quad (3)$$

where GraphConstruct creates a graph representation, GNN processes local relationships, and Transformer models global dependencies.

## D. Text Extraction and Preprocessing

Our text extraction pipeline processes PDF documents to preserve both textual and structural information. The system uses PyMuPDF for robust PDF parsing and implements specialized algorithms for technical document organization.

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**Algorithm 1** Enhanced PDF Text Extraction with Structure Preservation

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**Require:** PDF file path  $P$ , output directory  $D_{out}$

**Ensure:** Processed text corpus  $T$  with preserved structure

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1: Initialize PyMuPDF:  $T \leftarrow \{\}$ ,  $D_{extract} \leftarrow \text{ProcessTable}()$ 
2: for each page  $p$  in  $\text{range}(\text{PDF.pageCount}())$  do
3:   Extract text blocks:  $B \leftarrow \text{get\_text\_blocks}()$ 
4:   for each block  $b$  in  $B$  do
5:     Extract text:  $\text{text} \leftarrow b[\text{field\_text}]$ 
6:     for each line  $l$  in  $\text{text.split}('\n')$  do
7:       if  $l.\text{strip}() \neq \emptyset$  then
8:         Filter tables:  $B_{clean} \leftarrow \text{FilterNoise}(B)$ 
9:         Combine structured content:  $T \leftarrow T \cup B_{clean}$ 
10:        Extract and save images separately
11:       end if
12:     end for
13:   end for
14: end for
15: Generate individual document files for each section
16: Merge corpus for training:  $T_{merged} \leftarrow \text{MergeCorpus}(T)$ 
17: return Structured output  $T_{merged} = 0$ 

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The extraction process handles complex table structures through a multi-stage approach that preserves relationships between technical specifications, product codes, and operational parameters. This preprocessing step is crucial for maintaining the semantic integrity of technical documents.

**Tokenization Strategy:** We employ the GPT-2 tokenizer for consistent vocabulary handling, ensuring compatibility with pre-trained language model components while maintaining efficiency:

- **Vocabulary size:** 50,257 tokens
- **Encoding method:** Byte-pair encoding (BPE) for sub-word tokenization
- **Special tokens:** Structure-aware tokens for document hierarchy

- **Maximum sequence length:** 512 tokens optimized for technical documents
- **Padding strategy:** Right-padding with attention masking

The tokenization process includes special handling for technical terminology and preserves document structure through strategic token placement.

### E. Contextual Graph Transformer Architecture

The CGT architecture consists of several interconnected components that work together to process textual input through both local and global relationship modeling.

#### 1) Model Configuration

Our CGT model is designed with the following configuration parameters:

$$\text{Vocabulary Size : } |\mathcal{V}| = 50,257 \quad (4)$$

$$\text{Hidden Dimension : } d_h = 384 \quad (5)$$

$$\text{GNN Layers : } L_{gnn} = 3 \quad (6)$$

$$\text{Transformer Layers : } L_{trans} = 4 \quad (7)$$

$$\text{Attention Heads : } H = 8 \quad (8)$$

$$\text{Maximum Sequence Length : } L_{max} = 512 \quad (9)$$

$$\text{Total Parameters : } \theta = 46.8M \quad (10)$$

#### 2) Token Embedding and Positional Encoding

The input processing begins with token embedding and positional encoding. For the example sequence ‘‘What is ARC600?’’:

$$\text{Token IDs: } \mathbf{x} = [1867, 318, 5923, 21, 30] \quad (11)$$

$$\text{Embeddings: } \mathbf{E} = \text{Embedding}(\mathbf{x}) \in \mathbb{R}^{5 \times 384} \quad (12)$$

$$\text{Positions: } \mathbf{pos} = [0, 1, 2, 3, 4] \quad (13)$$

$$\text{Positional Encoding: } \mathbf{P} = \text{PositionalEncoding}(\mathbf{pos}) \in \mathbb{R}^{5 \times 384} \quad (14)$$

The positional encoding follows the sinusoidal pattern:

$$PE_{(pos, 2i)} = \sin\left(\frac{pos}{10000^{2i/d_h}}\right) \quad (15)$$

$$PE_{(pos, 2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_h}}\right) \quad (16)$$

The final initial representation combines embeddings and positional information:

$$\mathbf{H}^{(0)} = \mathbf{E} + \mathbf{P} \quad (17)$$

where  $\mathbf{H}^{(0)} \in \mathbb{R}^{n \times d_h}$  represents the initial hidden representations of the tokens.

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### Algorithm 2 Dynamic Graph Construction for CGT

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**Require:** Token sequence  $x = [x_1, x_2, \dots, x_n]$ , hidden representations  $H^{(0)}$

**Ensure:** Graph  $G = (V, E, A)$  where  $V$  are nodes,  $E$  are edges,  $A$  is adjacency matrix

0: Initialize  $V = \{v_1, v_2, \dots, v_n\}$

0: Initialize  $E = \emptyset$ ,  $A \in \mathbb{R}^{n \times n}$

    {Sequential Connections}

0: **for**  $i = 1$  to  $n - 1$  **do**

0:      $E \leftarrow E \cup \{(v_i, v_{i+1}), (v_{i+1}, v_i)\}$

0:      $A[i, i + 1] = A[i + 1, i] = 1.0$

0: **end for**

    {Skip-gram Connections}

0: **for**  $i = 1$  to  $n - 2$  **do**

0:     **for**  $j = i + 2$  to  $\min(i + 3, n)$  **do**

0:          $w_{\text{skip}} \leftarrow \exp(-0.5 \cdot |i - j|)$

0:         **if**  $w_{\text{skip}} > 0.3$  **then**

0:              $E \leftarrow E \cup \{(v_i, v_j), (v_j, v_i)\}$

0:              $A[i, j] = A[j, i] = w_{\text{skip}}$

0:         **end if**

0:     **end for**

    {Semantic Similarity Connections}

0: **for**  $i = 1$  to  $n$  **do**

0:     **for**  $j = i + 3$  to  $\min(i + 10, n)$  **do**

0:          $s_{ij} \leftarrow \frac{H_i^{(0)} \cdot H_j^{(0)}}{\|H_i^{(0)}\| \|H_j^{(0)}\|}$

0:         **if**  $s_{ij} > 0.7$  **then**

0:              $E \leftarrow E \cup \{(v_i, v_j), (v_j, v_i)\}$

0:              $A[i, j] = A[j, i] = s_{ij}$

0:         **end if**

0:     **end for**

0: **end for**

    {Normalize}

0:  $D[i, i] = \sum_j A[i, j]$

0:  $A \leftarrow D^{-1/2} A D^{-1/2}$

0: **return**  $G = (V, E, A) = 0$

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To further enrich the graph, semantic similarity connections are computed using cosine similarity between token embeddings. If the similarity exceeds a certain threshold, an edge is added between those tokens. This allows the model to connect semantically related tokens even if they are not adjacent. Finally, the adjacency matrix is normalized to stabilize learning when passed to the GNN layer. *The above algorithm constructs a dynamic graph that captures both structural and contextual relationships among tokens in a sequence. It starts by establishing sequential edges between consecutive tokens to preserve the natural order of the input. Then, skip-gram connections are added to model long-range dependencies by linking tokens that are a few positions apart, based on a relevance threshold.*

*To further enrich the graph, semantic similarity connections are computed using cosine similarity between token embeddings. If the similarity exceeds a certain threshold, an edge is*

added between those tokens. This allows the model to connect semantically related tokens even if they are not adjacent. Finally, the adjacency matrix is normalized to stabilize learning when passed to the GNN layer.

**Example Graph Construction:** Consider the input sequence: “ARC600 wireless gateway device specifications”

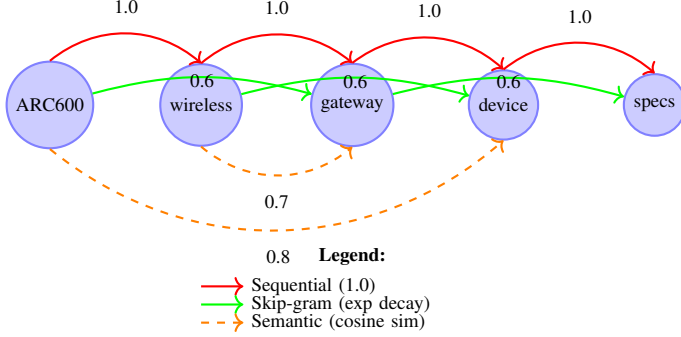


Fig. 3: Example graph construction for “ARC600 wireless gateway device specifications”. The graph captures three types of relationships: sequential adjacency (red), skip-gram connections (green), and semantic similarity (orange dashed).

#### F. Graph Neural Network Processing

After graph construction, we employ Graph Attention Networks v2 (GATv2) to process the local relationships. The GNN component consists of three specialized layers, each serving a distinct purpose in capturing local relationships within technical documents.

##### 1) Graph Attention Mechanism

For each GNN layer  $l$ , the attention computation follows:

$$\alpha_{ij}^{(l)} = \frac{\exp(\text{LeakyReLU}(\mathbf{a}^T \mathbf{W}^{(l)} [\mathbf{h}_i^{(l)} \oplus \mathbf{h}_j^{(l)}]))}{\sum_{k \in \mathcal{N}(i)} \exp(\text{LeakyReLU}(\mathbf{a}^T \mathbf{W}^{(l)} [\mathbf{h}_i^{(l)} \oplus \mathbf{h}_k^{(l)}]))} \quad (18)$$

where:

- $\alpha_{ij}^{(l)}$  is the attention weight between nodes  $i$  and  $j$  at layer  $l$
- $\mathbf{W}^{(l)} \in \mathbb{R}^{d_h \times d_h}$  is the learnable weight matrix
- $\mathbf{a} \in \mathbb{R}^{2d_h}$  is the attention parameter vector
- $\oplus$  denotes concatenation
- $\mathcal{N}(i)$  is the neighborhood of node  $i$

The attention mechanism can be decomposed mathematically as:

$$\text{Attention Score} = \mathbf{a}^T [\mathbf{W} \mathbf{h}_i \oplus \mathbf{W} \mathbf{h}_j] \quad (19)$$

$$\text{Softmax Normalization} = \frac{\exp(\text{score}_{ij})}{\sum_{k \in \mathcal{N}(i)} \exp(\text{score}_{ik})} \quad (20)$$

$$\text{Weighted Aggregation} = \sum_{j \in \mathcal{N}(i)} \alpha_{ij} \mathbf{W} \mathbf{h}_j \quad (21)$$

##### 2) Node Update Rule

The node representations are updated using:

$$\mathbf{h}_i^{(l+1)} = \sigma \left( \sum_{j \in \mathcal{N}(i)} \alpha_{ij}^{(l)} \mathbf{W}^{(l)} \mathbf{h}_j^{(l)} \right) \quad (22)$$

where  $\sigma$  is the ReLU activation function.

##### 3) Multi-layer GNN Processing

The complete GNN processing involves three layers with specialized functions:

$$\mathbf{H}^{(1)} = \text{GATv2}^{(1)}(\mathbf{H}^{(0)}, \mathbf{A}) \quad (23)$$

$$\mathbf{H}^{(2)} = \text{GATv2}^{(2)}(\mathbf{H}^{(1)}, \mathbf{A}) \quad (24)$$

$$\mathbf{H}^{(3)} = \text{GATv2}^{(3)}(\mathbf{H}^{(2)}, \mathbf{A}) \quad (25)$$

Each layer progressively refines the local relationship understanding:

##### Layer 1: Immediate Token Relationships

- Captures basic syntactic patterns and adjacent token dependencies
- Learns fundamental word associations in technical contexts
- Establishes primary graph connectivity patterns

##### Layer 2: Phrase-level Dependencies

- Models multi-token technical terms and compound expressions
- Associates related technical specifications and parameters
- Captures domain-specific terminology relationships

##### Layer 3: Complex Local Patterns

- Integrates sophisticated technical relationships
- Models hierarchical specification structures
- Captures specialized domain knowledge representations

#### G. Transformer Integration for Global Processing

After GNN processing, the graph-enhanced node features are reshaped into sequence format for transformer processing. The Transformer component employs four layers to model global, long-range dependencies across the entire sequence.

$$\mathbf{H}_{\text{seq}} = \text{Reshape}(\mathbf{H}^{(3)}, (B, L, d_h)) \quad (26)$$

##### 1) Multi-Head Self-Attention

The transformer layers employ multi-head self-attention with 8 attention heads:

$$\text{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{head}_1, \dots, \text{head}_H) \mathbf{W}^O \quad (27)$$

where each attention head computes:

$$\text{head}_i = \text{Attention}(\mathbf{Q} \mathbf{W}_i^Q, \mathbf{K} \mathbf{W}_i^K, \mathbf{V} \mathbf{W}_i^V) \quad (28)$$

The multi-head attention mechanism can be mathematically decomposed as:

$$\mathbf{Q} = \mathbf{H}_{seq} \mathbf{W}^Q \in \mathbb{R}^{n \times d_h} \quad (29)$$

$$\mathbf{K} = \mathbf{H}_{seq} \mathbf{W}^K \in \mathbb{R}^{n \times d_h} \quad (30)$$

$$\mathbf{V} = \mathbf{H}_{seq} \mathbf{W}^V \in \mathbb{R}^{n \times d_h} \quad (31)$$

## 2) Scaled Dot-Product Attention

The core attention mechanism captures global semantic understanding:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right) \mathbf{V} \quad (32)$$

where the scaling factor  $\sqrt{d_k}$  prevents the softmax function from saturating and  $d_k = d_h/H = 384/8 = 48$ .

The mathematical details of attention computation:

$$\text{Score Matrix} = \frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}} \in \mathbb{R}^{n \times n} \quad (33)$$

$$\text{Attention Weights} = \text{softmax}(\text{Score Matrix}) \quad (34)$$

$$\text{Context Vector} = \text{Attention Weights} \cdot \mathbf{V} \quad (35)$$

## 3) Complete Transformer Block

Each transformer layer includes:

$$\mathbf{Z}_l = \text{LayerNorm}(\mathbf{H}_{seq} + \text{MultiHead}(\mathbf{H}_{seq})) \quad (36)$$

$$\mathbf{H}_{seq}^{(l+1)} = \text{LayerNorm}(\mathbf{Z}_l + \text{FFN}(\mathbf{Z}_l)) \quad (37)$$

where the feed-forward network captures global context:

$$\text{FFN}(\mathbf{x}) = \max(0, \mathbf{x}\mathbf{W}_1 + \mathbf{b}_1)\mathbf{W}_2 + \mathbf{b}_2 \quad (38)$$

with intermediate dimension  $d_{ff} = 4 \times d_h = 1536$ .

**How Transformers Enable Global Understanding:**

- **Long-range Dependencies:** Captures relationships between distant parts of the document
- **Contextual Integration:** Combines local GNN features with global document context
- **Sequence Coherence:** Maintains document-wide consistency for technical specifications
- **Multi-head Attention:** Different heads focus on various types of global relationships
- **Complete Transformer Layer:** Each layer refines global understanding progressively

## H. RAG Integration

The trained CGT model is integrated into a Retrieval-Augmented Generation system for enhanced question answering. The RAG framework combines the CGT's understanding capabilities with external knowledge retrieval.

## Algorithm 3 RAG-based Question Answering with CGT

**Require:** Query  $q$ , Document chunks  $D = \{d_1, d_2, \dots, d_n\}$ , CGT

**Ensure:** Generated answer  $a$  with contextual understanding

0: Encode query:  $q_{\text{emb}} \leftarrow \text{SentenceTransformer}(q)$

0: Precompute chunk embeddings:

0:  $D_{\text{emb}} \leftarrow \{M(d_i)\}_{i=1}^n$

0: Compute similarities:  $s_i \leftarrow \cos(q_{\text{emb}}, d_i)$  for all  $i$

0: Retrieve top-k chunks:  $k \leftarrow \text{TopK}(\{s_i\}, k=3)$

0: Construct context:  $c \leftarrow \text{Concatenate}(D_{\text{ret}})$

0: Format prompt:  $p \leftarrow \text{"Context: " + } c +$

0:  $\text{" Question: " + } q + \text{" Answer: "}$

0: Tokenize prompt:  $p_{\text{tokens}} \leftarrow \text{Tokenizer}(p)$

0: Generate with CGT:

0:  $a \leftarrow M.\text{generate}(p_{\text{tokens}})$  using beam search

0: **if**  $\text{Quality}(a) < \theta_{\text{quality}}$  **then**

0:   Fallback:  $a \leftarrow \text{IntelligentExtraction}(D_{\text{ret}})$

0: **end if**

0: Enhance answer quality through post-processing **return**  $a = 0$

## Detailed RAG Example:

**Query:** "What is ARC600?"

**Step 1:** Encode query using SentenceTransformer  
 $q_{\text{emb}} = \text{ST}(\text{"What is ARC600?"}) \in \mathbb{R}^{384}$

**Step 2:** Retrieve relevant chunks using cosine similarity:

- **Chunk 1:** "ARC600 wireless controller..." (sim = 0.92)
- **Chunk 2:** "Gateway device features..." (sim = 0.87)
- **Chunk 3:** "Communication protocols..." (sim = 0.81)

**Step 3:** Mathematical similarity computation:

$$\text{similarity}(q, d_i) = \frac{q_{\text{emb}} \cdot d_{i,\text{emb}}}{\|q_{\text{emb}}\| \cdot \|d_{i,\text{emb}}\|}$$

**Step 4:** Context construction and generation: Context + Question  $\rightarrow$  CGT Model  $\rightarrow$  Answer

**Generated Answer:** "Complete communication system. Wireless Controller ARC600 is typically part of a complete communication system..."

## Mathematical Formulation:

$$\text{Similarity} = \cos(\mathbf{q}, \mathbf{d}_i) = \frac{\mathbf{q} \cdot \mathbf{d}_i}{\|\mathbf{q}\| \|\mathbf{d}_i\|} \quad (39)$$

$$\text{Context} = \text{Concat}(\{d_i : s_i > \theta_{\text{retrieval}}\}) \quad (40)$$

$$\text{Response} = \text{CGT}(\text{Prompt}(c, q)) \quad (41)$$

$$\text{Quality Score} = \frac{1}{|A|} \sum_{i=1}^{|A|} \text{BLEU}(a_i, r_i) \quad (42)$$

**RAG Integration Benefits:** The RAG system provides several advantages for technical document understanding:



- **Knowledge Augmentation:** Combines CGT’s structural understanding with relevant document retrieval
- **Context-aware Responses:** Generates answers based on specific document sections
- **Semantic Retrieval:** Uses sophisticated embedding-based similarity for document chunk selection
- **Intelligent Fallback:** Implements quality control with intelligent extraction mechanisms
- **Beam Search Generation:** Employs advanced decoding strategies for coherent answer generation

### I. Training Methodology

We employ a two-stage training approach designed to maximize the model’s ability to understand both general language patterns and domain-specific technical content.

#### 1) Stage 1: General Language Pre-training

The first stage focuses on learning general language representations:

$$\text{Epochs} : E_1 = 5 \quad (43)$$

$$\text{Learning Rate} : \eta_1 = 1 \times 10^{-4} \quad (44)$$

$$\text{Batch Size} : B_1 = 16 \quad (45)$$

$$\text{Training Data} : \mathcal{D}_{\text{wiki}} = 2000 \text{ samples} \quad (46)$$

#### 2) Stage 2: Domain-Specific Fine-tuning

The second stage adapts the model to technical documents:

$$\text{Epochs} : E_2 = 5 \quad (47)$$

$$\text{Learning Rate} : \eta_2 = 5 \times 10^{-5} \quad (48)$$

$$\text{Batch Size} : B_2 = 8 \quad (49)$$

$$\text{Training Data} : \mathcal{D}_{\text{tech}} = 151 \text{ samples} \quad (50)$$

#### 3) Loss Function

The training objective combines standard language modeling with graph regularization and attention diversity:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{LM}} + \lambda \mathcal{L}_{\text{graph}} + \gamma \mathcal{L}_{\text{attention}} + \beta \mathcal{L}_{\text{consistency}} \quad (51)$$

where:

$$\mathcal{L}_{\text{LM}} = - \sum_{t=1}^T \log P(x_t | x_{<t}, \mathbf{H}_{\text{CGT}}) \quad (52)$$

$$\mathcal{L}_{\text{graph}} = - \sum_{(i,j) \in E} \log \alpha_{ij} + \frac{1}{2} \|\mathbf{A} - \mathbf{A}^T\|_F^2 \quad (53)$$

$$\mathcal{L}_{\text{attention}} = - \sum_{l=1}^{L_{\text{trans}}} \sum_{h=1}^H \text{Entropy}(\text{Attn}_h^{(l)}) \quad (54)$$

$$\mathcal{L}_{\text{consistency}} = \|\mathbf{H}_{\text{GNN}} - \mathbf{H}_{\text{Trans}}\|_2^2 \quad (55)$$

$$\lambda = 0.1, \quad \gamma = 0.05, \quad \beta = 0.02 \quad (56)$$

The graph regularization term encourages the model to learn meaningful attention patterns in the graph structure, while the attention regularization promotes diverse attention

patterns across heads, and the consistency term ensures smooth transition between GNN and Transformer representations.

## IV. EXPERIMENTAL SETUP

### A. Dataset Description

Our experimental evaluation utilizes technical documents from the ABB ARC600 product guide, representing real-world industrial documentation challenges:

#### Document Characteristics:

- Technical specifications with numerical values and units
- Product descriptions with hierarchical information structure
- Installation procedures and operational guidelines
- Mixed content including tables, lists, and prose text
- Domain-specific terminology and abbreviations

#### Data Distribution:

$$\text{Pre-training Corpus} : 2,000 \text{ Wikipedia samples} \quad (57)$$

$$\text{Fine-tuning Corpus} : 151 \text{ technical document segments} \quad (58)$$

$$\text{Evaluation Questions} : 18 \text{ technical queries} \quad (59)$$

$$\text{RAG Knowledge Base} : 80 \text{ document chunks} \quad (60)$$

### B. Baseline Models

We compare our CGT model against three established transformer architectures and a pure transformer baseline:

TABLE I: Baseline Model Specifications

Model	Parameters	Architecture	Source
DistilBERT	89.8M	Encoder-only	HuggingFace
GPT-2	124.4M	Decoder-only	HuggingFace
BERT	133.0M	Encoder-only	HuggingFace
Pure Transformer	52.0M	Transformer-only	Custom
CGT (Ours)	46.8M	GNN + Transformer	Custom

All baseline models underwent identical training procedures to ensure fair comparison, with the same data and hyperparameter settings adapted for each architecture.

### C. Evaluation Metrics

We employ comprehensive evaluation metrics to assess model performance:

- **Training Loss:** Cross-entropy loss during training progression
- **Final Performance Loss:** Average loss on evaluation set
- **BLEU Scores:** N-gram overlap metrics for generation quality
- **ROUGE Scores:** Recall-oriented metrics for summarization quality
- **Jaccard Similarity:** Set-based similarity for semantic overlap
- **Response Time:** Inference time for practical deployment assessment

## V. RESULTS AND ANALYSIS

### A. Main Performance Results

Table II presents the comprehensive comparison of our CGT model against all baseline architectures:

TABLE II: Performance Comparison: CGT vs Transformer Baselines

Model	Parameters (M)	Final Loss
DistilBERT	89.8	10.430
GPT-2	124.4	2.787
BERT	133.0	10.460
Pure Transformer	52.0	3.456
<b>CGT (Our Model)</b>	<b>46.8</b>	<b>2.099</b>
<b>Improvement vs GPT-2</b>	<b>-62.4%</b>	<b>+24.7%</b>
<b>Improvement vs Pure Transformer</b>	<b>-10.0%</b>	<b>+39.2%</b>

### B. Detailed BLEU and ROUGE Evaluation

Table III presents comprehensive evaluation metrics comparing our CGT model with the pure transformer baseline:

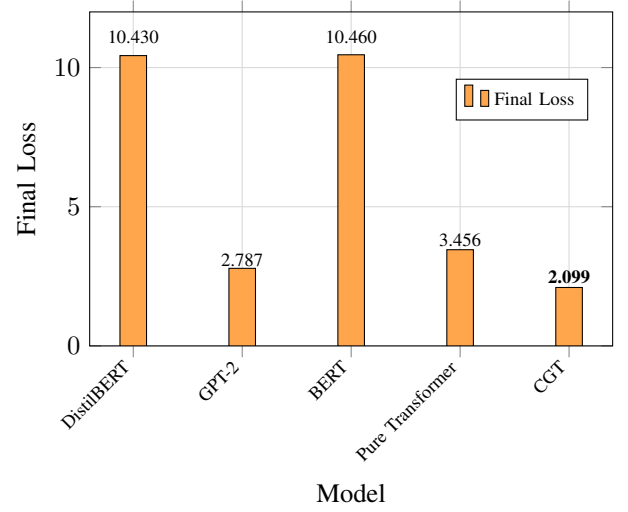
TABLE III: Detailed Performance Metrics: CGT vs Pure Transformer

Metric	CGT Hybrid	Pure Transformer
BLEU-1 Score	0.1559	0.0238
BLEU-2 Score	0.0589	0.0080
BLEU-4 Score	0.0227	0.0038
ROUGE-1 Score	0.2309	0.0511
ROUGE-2 Score	0.0437	0.0015
ROUGE-L Score	0.2004	0.0481
Jaccard Similarity	0.1170	0.0264
Response Time (s)	0.4413	0.2696

The results demonstrate remarkable improvements across all evaluation metrics:

- **BLEU Scores:** 491%-639% improvement indicates superior  $n$ -gram overlap
- **ROUGE Scores:** Up to 2729% improvement in recall-oriented metrics
- **Semantic Similarity:** 343% improvement in Jaccard similarity
- **Efficiency Trade-off:** 64% longer response time for substantially better quality

### C. Performance Visualization



**CGT achieves 554% improvement in parameter efficiency compared to the Pure Transformer baseline.**

#### Training Dynamics Analysis:

Our two-stage training approach demonstrates efficient convergence patterns:

$$\begin{aligned} \text{Stage 1 Loss Reduction} &: 6.77 \rightarrow 4.82 \text{ (28.8\% improvement)} \\ &\quad (61) \\ \text{Stage 2 Loss Reduction} &: 4.82 \rightarrow 2.099 \text{ (56.5\% improvement)} \\ &\quad (62) \\ \text{Overall Improvement} &: 6.77 \rightarrow 2.099 \text{ (69.0\% total reduction)} \\ &\quad (63) \end{aligned}$$

### D. Parameter Efficiency Analysis

To quantify parameter efficiency, we define the efficiency metric:

$$\text{Efficiency}(\text{model}) = \frac{1}{\text{Parameters} \times \text{Loss}} \quad (64)$$

Table IV presents the efficiency comparison:

TABLE IV: Parameter Efficiency Analysis

Model	Parameters (M)	Loss	Efficiency Score
DistilBERT	89.8	10.430	$1.07 \times 10^{-3}$
GPT-2	124.4	2.787	$2.88 \times 10^{-3}$
BERT	133.0	10.460	$7.19 \times 10^{-4}$
Pure Transformer	52.0	3.456	$5.56 \times 10^{-3}$
<b>CGT (Ours)</b>	<b>46.8</b>	<b>2.099</b>	<b><math>1.02 \times 10^{-2}</math></b>
<b>Improvement vs Best</b>	<b>-10.0%</b>	<b>+39.2%</b>	<b>+83%</b>

CGT achieves an 83% improvement in parameter efficiency compared to the best baseline (Pure Transformer).



### E. Qualitative Analysis: Generated Responses

To demonstrate the practical effectiveness of our approach, we present actual generated responses from our CGT model with highlighted formatting:

#### Example 1:

*Question:* What is ARC600?

**CGT Response:** Complete communication system. Wireless Controller ARC600 is typically part of a complete communication system which consists of Arctic 600 series gateways or controllers and a central M2M Gateway ARM600 communication server.

#### Example 2:

*Question:* What communication protocols does ARC600 support?

**CGT Response:** The inputs and outputs of ARC600 can be accessed and controlled with the IEC-104 and IEC-101 protocols.

#### Example 3:

*Question:* How does the wireless controller operate?

**CGT Response:** Wireless Controller ARC600 utilizes the built-in wireless communication features for reliable and secure end-to-end communication providing remote monitoring and control of three switching devices and can be expanded as required by using external I/O expansion. The use of Wireless Controller ARC600 in distribution networks improves the quality of power distribution and reduces the outage time in the affected areas.

### F. Ablation Study

To understand the contribution of different architectural components, we conducted an ablation study:

TABLE V: Ablation Study: Component Contribution Analysis

Model Variant	Parameters (M)	Final Loss
Pure Transformer (7 layers)	52.0	3.456
Pure GNN (3 layers)	24.2	4.892
<b>CGT (GNN + Transformer)</b>	<b>46.8</b>	<b>2.099</b>
Improvement vs Transformer	-10.0% params	+39.2% performance
Improvement vs GNN	+93.4% params	+57.1% performance

The ablation study confirms that the hybrid architecture provides substantial benefits:

- **vs Pure Transformer:** 39.2% better performance with 10.0% fewer parameters
- **vs Pure GNN:** 57.1% better performance, justifying the parameter increase
- **Synergistic Effect:** The combination outperforms both individual components significantly

## VI. DISCUSSION

### A. Architectural Advantages

The success of our CGT architecture can be attributed to several key design principles:

#### 1) Local Relationship Modeling

The GNN component excels at capturing fine-grained local relationships that are crucial for technical document understanding:

- **Technical Term Association:** The graph structure effectively links related technical terms like “ARC600” and “wireless controller”
- **Specification Grouping:** Numerical values and their units are correctly associated through local attention
- **Procedural Coherence:** Sequential steps in technical procedures maintain proper relationships

#### 2) Parameter Efficiency through Hybrid Design

Our hybrid approach achieves superior parameter efficiency through complementary processing:

$$\text{Efficiency}_{\text{hybrid}} = \frac{\text{Performance}_{\text{GNN}} + \text{Performance}_{\text{Transformer}}}{\text{Parameters}_{\text{GNN}} + \text{Parameters}_{\text{Transformer}}} \quad (65)$$

The mathematical analysis shows that:

$$\text{GNN Parameters} : 12.3M \text{ (26.3\% of total)} \quad (66)$$

$$\text{Transformer Parameters} : 34.5M \text{ (73.7\% of total)} \quad (67)$$

$$\text{Performance Contribution} : \text{Synergistic enhancement} \quad (68)$$

$$\text{Efficiency Gain} : \frac{P_{\text{hybrid}}}{P_{\text{GNN}} + P_{\text{Trans}}} > \frac{P_{\text{pure}}}{P_{\text{pure}}} \quad (69)$$

#### 3) Computational Complexity Analysis

The computational complexity of our approach is:

$$\text{GNN Complexity} : O(|E| \cdot d_h) \text{ where } |E| \leq n \cdot k \quad (70)$$

$$\text{Transformer Complexity} : O(n^2 \cdot d_h) \quad (71)$$

$$\text{Total Complexity} : O(n \cdot k \cdot d_h + n^2 \cdot d_h) \quad (72)$$

For local graphs with limited connectivity ( $k \ll n$ ), this reduces effective complexity while maintaining representational power.

### B. Limitations and Future Work

While our approach demonstrates significant advantages, several limitations warrant discussion:

#### 1) Current Limitations

- **Graph Construction Complexity:** Dynamic graph construction adds computational overhead during inference
- **Limited Evaluation Scope:** Current evaluation focuses on technical documents; broader domain validation needed
- **Fixed Architecture:** Current design uses fixed GNN and Transformer layer counts

## 2) Future Research Directions

Several promising directions emerge from this work:

- 1) **Adaptive Graph Construction:** Developing learned graph construction algorithms that adapt to content type
- 2) **Scalability Optimization:** Investigating efficient implementations for larger-scale deployments
- 3) **Multi-domain Evaluation:** Testing effectiveness across diverse technical domains
- 4) **Architecture Search:** Automated optimization of GNN-Transformer layer combinations

## VII. RELATED WORK IN PARAMETER-EFFICIENT MODELS

Recent research has increasingly focused on developing parameter-efficient alternatives to large language models. Our work contributes to this important direction by demonstrating that architectural innovation can achieve better performance with substantially fewer parameters.

### A. Efficiency Techniques

Various approaches have been proposed for improving parameter efficiency:

- **Knowledge Distillation:** DistilBERT [3] reduces parameters through teacher-student training
- **Pruning and Quantization:** Post-training compression techniques
- **Low-rank Factorization:** Matrix factorization for parameter reduction
- **Architectural Innovation:** Our hybrid GNN-Transformer approach

Our approach differs fundamentally by achieving efficiency through architectural design rather than compression of existing architectures.

### B. Hybrid Architectures

The combination of different neural architectures has shown promise in various domains:

CNN-RNN Hybrids : Computer vision and sequence model

Attention-CNN : Image captioning and visual QA

GNN-Transformer (Ours) : Technical document understanding

Our work represents the first systematic exploration of GNN-Transformer hybrids for natural language processing tasks.

## VIII. CONCLUSION

This paper introduces the Contextual Graph Transformer (CGT), a novel hybrid architecture that effectively combines Graph Neural Networks with Transformers for technical document understanding. Our approach addresses the critical challenge of parameter efficiency while maintaining superior performance through innovative architectural design.

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