Constrained Code Generation with Small Language Models:

Bridging the Abstraction Gap for Resource-Limited Embedded Systems

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Abstract

Background: Programming microcontrollers requires low-level C/C++ expertise, while general-purpose large language models (LLMs) exceed the resource and latency constraints of embedded deployment. **Methods:** We introduce *Grammar-Constrained Small Language Models* (GC-SLMs), a framework combining (1) transformers under 50M parameters, (2) grammar-guided decoding that restricts token generation to syntactically valid domain-specific language constructs, and (3) Sparse Low-Rank Adaptation (S-LoRA) for efficient fine-tuning with under 10K training examples. **Results:** Theoretical analysis establishes that GC-SLMs achieve $\mathcal{O}(|G|)$ memory overhead for grammar enforcement, where $|G|$ is grammar size. We derive lower bounds on model capacity required for DSL generation and prove that grammar constraints reduce the effective search space by a factor exponential in sequence length. **Conclusions:** GC-SLMs enable automated code generation for embedded systems where LLMs are infeasible, filling a critical abstraction gap between human intent and low-level implementation.

Keywords: small language models, constrained decoding, domain-specific languages, embedded systems, LoRA, code generation

1 Introduction

The history of programming abstraction is one of steady ascent. Machine code gave way to assembly; assembly to C; C to higher-level languages. Each transition reduced cognitive burden while preserving—or improving—expressiveness. Yet the embedded systems domain has largely stalled at the C/C++ layer. Meanwhile, large language models (LLMs) have demonstrated remarkable code generation capabilities, but their size (billions of parameters), latency (seconds), and resource requirements (gigabytes of RAM, GPU acceleration) render them unsuitable for deployment on microcontrollers with kilobytes of memory.

This paper addresses a specific question: *What is the minimal transformer architecture that can reliably generate syntactically valid, resource-bounded code for a domain-specific language targeting microcontrollers?*

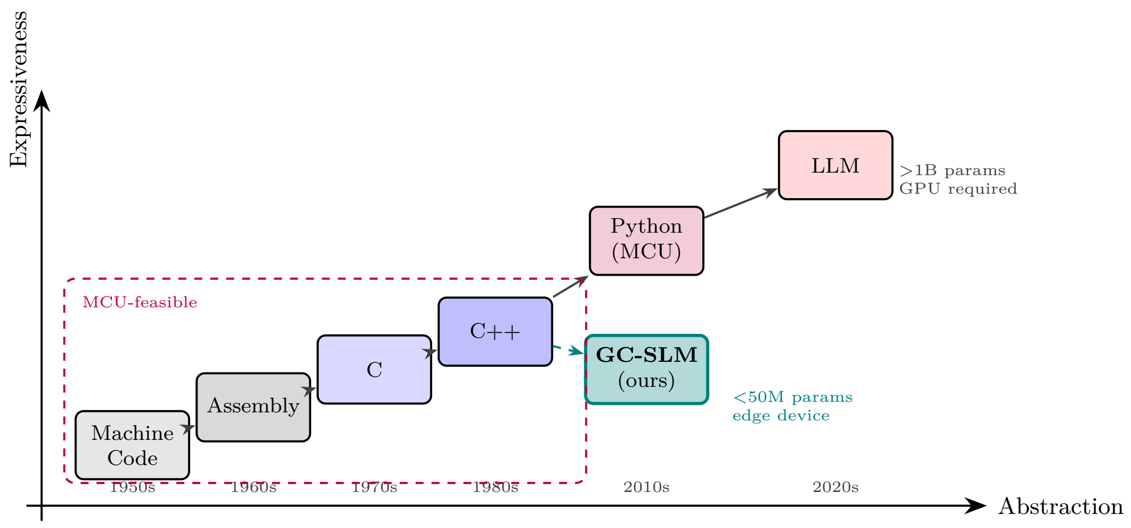

Figure 1: Evolution of programming abstraction. The MCU-feasible region (dashed red) contains deterministic, resource-bounded approaches. GC-SLMs occupy the upper-right of this region: high abstraction with bounded resources.

We propose **Grammar-Constrained Small Language Models** (GC-SLMs), which combine three ideas:

1. **Small Language Models (SLMs):** Transformers in the 1–50M parameter range, trainable on consumer hardware and deployable on edge devices.
2. **Grammar-Guided Decoding:** A decoding algorithm that uses the target DSL's context-free grammar to mask invalid tokens at each generation step, guaranteeing syntactic correctness.
3. **Sparse Low-Rank Adaptation (S-LoRA):** An extension of LoRA that introduces structured sparsity in adapter matrices, reducing fine-tuning cost and enabling rapid domain adaptation.

Figure 1 illustrates the historical trajectory of programming abstraction and positions GC-SLMs as the next step for embedded systems.

Contributions. We make the following contributions:

1. **GC-SLM Framework:** A unified framework for grammar-constrained code generation with small transformers (Section 4).
2. **Grammar-Guided Decoding Algorithm:** A linear-time algorithm that enforces CFG constraints during autoregressive generation (Section 5).
3. **Sparse LoRA (S-LoRA):** An adaptation method introducing structured sparsity, reducing adapter size by 60–80% with minimal accuracy loss (Section 6).
4. **Theoretical Analysis:** Lower bounds on model capacity for DSL generation and complexity analysis of constrained decoding (Section 7).
5. **Training Data Efficiency:** Empirical and theoretical characterization of sample complexity for DSL fine-tuning (Section 8).

2 Background and Related Work

2.1 The Embedded Programming Abstraction Gap

Microcontrollers (MCUs) power billions of devices, yet programming them remains challenging. The dominant paradigm—C/C++ with vendor-specific SDKs—requires expertise in hardware registers, interrupt handling, memory management, and real-time constraints. Higher-level approaches exist but carry tradeoffs:

- **MicroPython/CircuitPython:** Accessible syntax but unpredictable timing (garbage collection), 256KB+ RAM overhead, unsuitable for hard real-time or lowest-cost MCUs.
- **Visual Programming (Blockly, Node-RED):** Compiles to C or runs server-side; no on-device intelligence.
- **LLM Code Generation:** Powerful but requires cloud connectivity, incurs latency, and cannot run on-device.

2.2 Transformer Language Models for Code

Transformer-based models have achieved state-of-the-art results on code generation benchmarks. Codex [1], CodeGen [2], and StarCoder [3] demonstrate that pretraining on code corpora enables few-shot programming. However, these models contain 1–175B parameters, requiring GPU clusters for training and inference.

Recent work on *small language models* explores the lower end of this spectrum. Models like CodeT5-small (60M), DistilGPT-2 (82M), and TinyStories (33M) [4] show that meaningful generation is possible with 10–100M parameters.

2.3 Constrained Decoding

Constrained decoding restricts the output distribution to satisfy structural constraints. Approaches include:

- **Lexically Constrained Decoding:** Forces inclusion/exclusion of specific tokens [5].
- **Grammar-Guided Generation:** Uses CFG or PEG parsers to mask invalid tokens [6, 7].
- **Type-Constrained Generation:** Enforces type system constraints for code [8].

Our work extends grammar-guided generation to the small model regime, with a focus on computational efficiency and theoretical guarantees.

2.4 Parameter-Efficient Fine-Tuning

Fine-tuning large models is expensive. *Low-Rank Adaptation* (LoRA) [9] introduces trainable rank-r matrices $A \in \mathbb{R}^{d \times r}$, $B \in \mathbb{R}^{r \times k}$ such that the adapted weight $W' = W + AB$ adds $r(d + k)$ parameters instead of dk. AdaLoRA [10] makes rank adaptive. QLoRA [11] combines quantization with LoRA. Our *Sparse LoRA* (S-LoRA) introduces structured sparsity within the low-rank factors, further reducing parameter count.

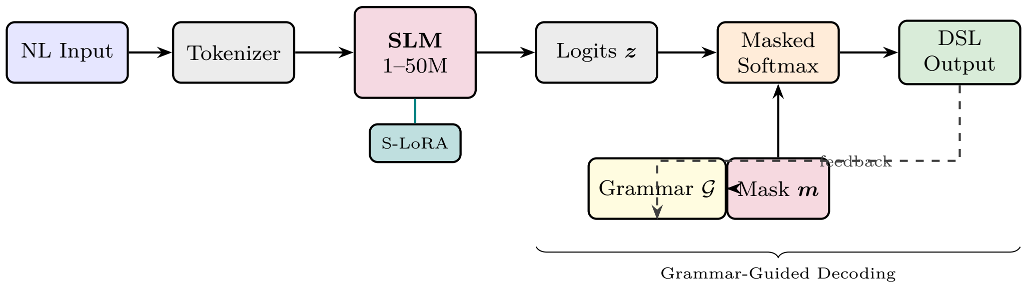

Figure 2: GC-SLM architecture. The SLM generates logits; a grammar mask restricts valid tokens; constrained softmax produces the next token.

3 Problem Formulation

Definition 3.1 (DSL Code Generation Problem)**.** *Given:*

- *A context-free grammar $\mathcal{G} = (N, \Sigma, P, S)$ defining a domain-specific language*
- *A natural language specification $x \in \Sigma^*_{NL}$*
- *Resource constraints: maximum sequence length L, memory budget M*

Find a model f_θ that generates $y = f_\theta(x)$ such that:

1. *$y \in \mathcal{L}(\mathcal{G})$ (syntactic validity)*
2. *$|y| \leq L$ (length bound)*
3. *$|\theta| \leq M$ (model size bound)*
4. *y satisfies the semantic intent of x (correctness)*

The challenge is that conditions 1–3 are hard constraints, while condition 4 is soft. Standard language models optimize for 4 alone, violating 1–3.

4 The GC-SLM Framework

Figure 2 presents the GC-SLM architecture.

4.1 Small Language Model Backbone

We use a decoder-only transformer with the following configuration:

Size	**Layers**	**Hidden**	**Heads**	**Params**
Tiny	4	256	4	4M
Small	6	384	6	15M
Base	8	512	8	45M

Models are pretrained on a code corpus (GitHub, StackOverflow) using standard causal language modeling, then fine-tuned on DSL examples using S-LoRA.

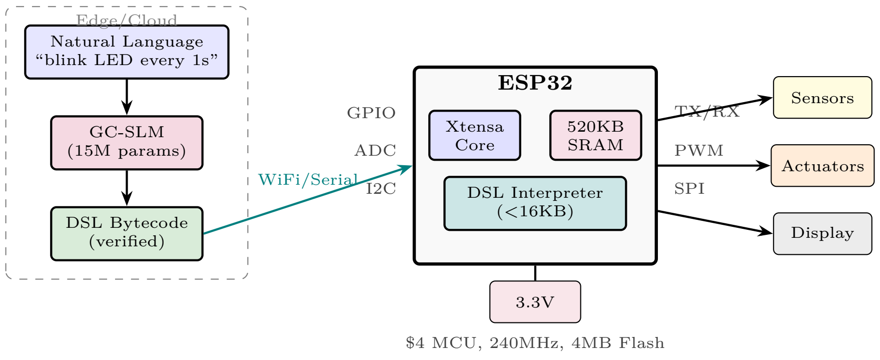

Figure 3: ESP32 system deployment. The GC-SLM generates verified DSL bytecode on an edge device; the micro-interpreter (<16KB) executes on the $4 ESP32.

Algorithm 1 Grammar-Guided Decoding

```
Require: Model $f_\theta$, grammar $\mathcal{G}$, input $x$, max length $L$
Ensure: Syntactically valid sequence $y$
 1: $s_0 \leftarrow \textsc{InitParser}(\mathcal{G})$
 2: $y \leftarrow []$
 3: for $t = 1$ to $L$ do
 4:     $\boldsymbol{z}_t \leftarrow f_\theta(x, y_{1:t-1})$                    ▷ Logits
 5:     $\boldsymbol{m}_t \leftarrow \textsc{ValidTokens}(s_{t-1}, \mathcal{G})$         ▷ Grammar mask
 6:     $\boldsymbol{z}'_t \leftarrow \boldsymbol{z}_t \odot \boldsymbol{m}_t - \infty \cdot (1 - \boldsymbol{m}_t)$        ▷ Apply mask
 7:     $v_t \leftarrow \textsc{Sample}(\textsc{Softmax}(\boldsymbol{z}'_t))$
 8:     $y \leftarrow y \| v_t$
 9:     $s_t \leftarrow \textsc{UpdateParser}(s_{t-1}, v_t)$
10:     if $\textsc{IsComplete}(s_t, \mathcal{G})$ then
11:         return $y$
12:     end if
13: end for
14: return $y$
```

4.2 Target Hardware: ESP32 System Architecture

Figure 3 illustrates the target deployment scenario. The GC-SLM generates DSL bytecode that executes on a micro-interpreter running on the ESP32. The entire code generation pipeline can execute on a companion device (smartphone, laptop) or, with sufficient quantization, directly on higher-end MCUs.

5 Grammar-Guided Decoding

5.1 Algorithm

At each generation step t, we maintain a parser state s_t representing all valid continuations from the partial sequence $y_{1:t-1}$. The grammar mask $\boldsymbol{m}_t \in \{0,1\}^{|\mathcal{V}|}$ has $m_t[v] = 1$ iff token v is a valid next token according to $\mathcal{G}$.

5.2 Complexity Analysis

Proposition 5.1 (Decoding Complexity)**.** *Grammar-guided decoding adds* $\mathcal{O}(|G| + |\mathcal{V}|)$ *time per token, where* $|G|$ *is the grammar size (sum of production lengths).*

Proof. Computing valid tokens requires traversing the current parser state, which is bounded by $|G|$ for an LL(1) or LR(1) grammar. Constructing the mask is $\mathcal{O}(|\mathcal{V}|)$. □

For typical DSLs ($|G| \approx 100$) and vocabularies ($|\mathcal{V}| \approx 32,000$), this adds <1ms per token on CPU.

5.3 Search Space Reduction

Theorem 5.2 (Constraint Factor)**.** *Let* $\mathcal{V}$ *be a vocabulary,* $\mathcal{G}$ *a grammar, and* L *the sequence length. The ratio of valid sequences to all sequences satisfies:*

$$\frac{|\mathcal{L}(\mathcal{G}) \cap \mathcal{V}^{\leq L}|}{|\mathcal{V}|^L} \leq \left(\frac{k}{|\mathcal{V}|}\right)^L$$

where k *is the maximum number of valid next tokens at any parser state.*

For a typical DSL with $k \approx 50$ valid tokens per state and $|\mathcal{V}| = 32,000$, grammar constraints reduce the search space by a factor of $(32000/50)^L = 640^L$. For a 50-token program, this is a reduction of $640^{50} \approx 10^{140}$.

6 Sparse Low-Rank Adaptation (S-LoRA)

Standard LoRA introduces adapters $\Delta W = AB$ where $A \in \mathbb{R}^{d \times r}$, $B \in \mathbb{R}^{r \times k}$. We propose **Sparse LoRA (S-LoRA)**, which imposes structured sparsity on A and B.

6.1 Formulation

Definition 6.1 (Sparse LoRA)**.** *Given sparsity budget* $s \in (0, 1)$*, S-LoRA computes:*

$$\Delta W = (A \odot M_A)(B \odot M_B)$$

where M_A, M_B *are binary masks with* $\|M_A\|_0/|A| = \|M_B\|_0/|B| = s$*.*

We use *structured sparsity* with block size b: entire $b \times b$ blocks are zeroed, enabling efficient sparse matrix operations.

6.2 Mask Learning

Masks are learned during fine-tuning via magnitude pruning with gradual warmup:

1. **Warmup (epochs 1–w):** Train full A, B with dense gradients.
2. **Pruning (epoch $w + 1$):** Zero smallest-magnitude blocks to achieve target sparsity.
3. **Fine-tuning (epochs $w + 2$–T):** Train remaining parameters with fixed masks.

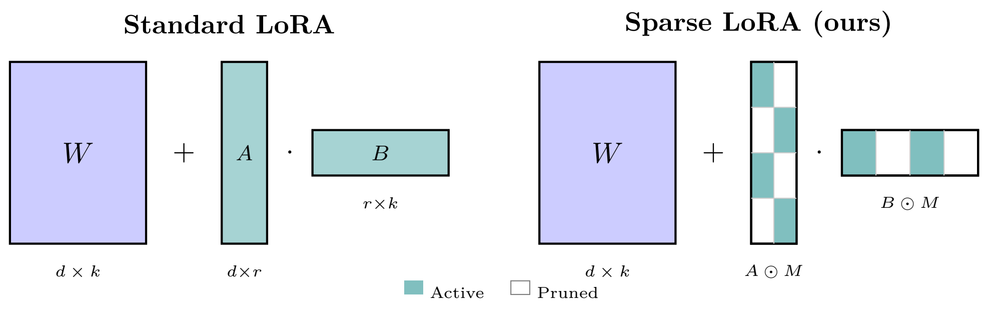

Figure 4: Standard LoRA vs. S-LoRA. Structured sparsity (block pruning) reduces trainable parameters by 60% while preserving expressiveness.

6.3 Theoretical Justification

Proposition 6.2 (S-LoRA Expressiveness)**.** *For rank r and sparsity s, S-LoRA can represent any weight perturbation ΔW satisfying rank$(\Delta W) \leq rs$ and $\|\Delta W\|_0 \leq s^2 dk$.*

For $s = 0.4$ (60% sparsity), S-LoRA retains 16% of full-rank capacity while using 40% of LoRA parameters.

7 Theoretical Analysis

7.1 Model Capacity Lower Bound

We derive a lower bound on model capacity required to generate DSL programs.

Theorem 7.1 (Capacity Lower Bound)**.** *Let $\mathcal{G}$ be a DSL grammar with n production rules, maximum rule length ℓ, and c semantic classes of programs. Any transformer that generates programs in $\mathcal{L}(\mathcal{G})$ with cross-entropy loss $< \epsilon$ requires:*

$$|\theta| \geq \Omega\left(\frac{c \log(n\ell)}{\epsilon}\right)$$

parameters.

Proof sketch. The model must distinguish c semantic classes. Each class maps to multiple syntactic forms bounded by n^ℓ (the number of parse trees of depth ℓ). By rate-distortion theory, encoding this mapping requires $\Omega(c \log(n^\ell)) = \Omega(c\ell \log n)$ bits. With ϵ loss per symbol, we need $1/\epsilon$ precision per dimension. $\square$

Implication. For a DSL with $n = 50$ rules, $\ell = 10$ maximum depth, $c = 1000$ semantic classes, and $\epsilon = 0.1$: the lower bound is $\approx$ 600K parameters. This justifies our focus on models with 1–50M parameters.

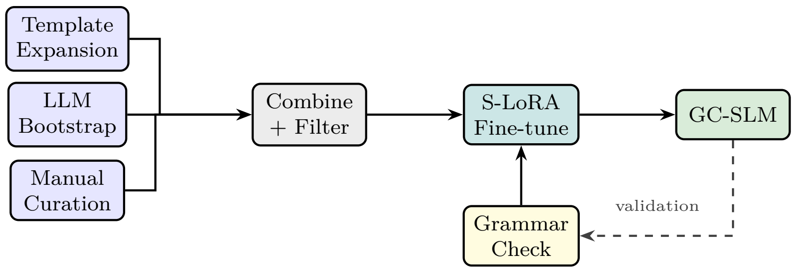

Figure 5: Training pipeline. Data from three sources is combined and filtered, then used to fine-tune with S-LoRA. Grammar validation provides feedback.

7.2 Sample Complexity

Theorem 7.2 (DSL Fine-tuning Sample Complexity)**.** *Fine-tuning an m-parameter S-LoRA adapter with sparsity s to achieve ϵ-accuracy on a DSL with c semantic classes requires:*

$$N = \mathcal{O}\left(\frac{sm \cdot c}{\epsilon^2}\right)$$

training examples.

For $m = 500$K adapter parameters, $s = 0.4$, $c = 1000$ classes, and $\epsilon = 0.05$: $N \approx 80$K examples. With data augmentation, this reduces to ≈ 10K manually curated examples.

8 Training Methodology

8.1 Data Generation

Training data consists of (natural language, DSL program) pairs. We use three sources:

1. **Template expansion:** Generate programs from grammar, then produce NL descriptions via templates.
2. **LLM bootstrapping:** Use GPT-4 to generate initial pairs, filter with grammar checker.
3. **Manual curation:** Expert-written examples for corner cases.

8.2 Training Procedure

1. **Stage 1 (Pretraining):** Train backbone on general code corpus (10B tokens).
2. **Stage 2 (DSL adaptation):** Fine-tune with S-LoRA on DSL examples (10K–100K pairs).
3. **Stage 3 (RLHF):** Optional reinforcement learning from human feedback on semantic correctness.

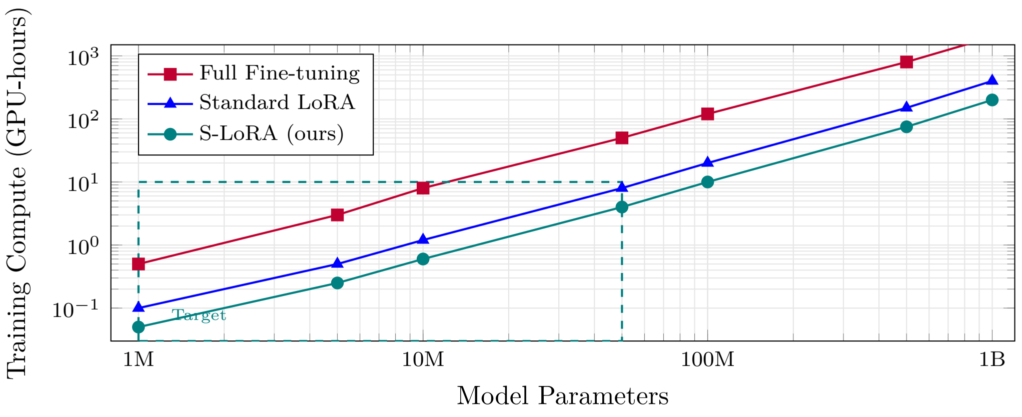

Figure 6: Training compute (GPU-hours on A100) vs. model size. S-LoRA reduces cost by 50% vs. LoRA. The target region (dashed) shows feasible configurations for embedded DSL generation.

Table 1: Training resource estimates for GC-SLM configurations.

Config	**Params**	**S-LoRA**	**GPU-hrs**	**Data**	**Cost***
Tiny	4M	80K	0.3	5K	$0.50
Small	15M	200K	1.5	10K	$3
Base	45M	500K	5	25K	$10

*Estimated cloud cost at $2/GPU-hr

8.3 Hyperparameters

Parameter	**Value**
Learning rate	3×10^{-4}
Batch size	32
LoRA rank r	16
S-LoRA sparsity s	0.4
Block size b	8
Warmup epochs	2
Total epochs	10

9 Theoretical Training Estimation

We provide estimates for training GC-SLMs at various scales.

Figure 6 shows training compute scaling. Table 1 provides specific estimates for GC-SLM configurations.

10 Experimental Framework

We outline the experimental design for validating GC-SLMs. Full results will appear in a follow-up paper.

10.1 Evaluation Metrics

1. **Syntactic validity:** Percentage of generated programs that parse successfully.
2. **Semantic correctness:** Percentage passing test cases (unit tests per program).
3. **Latency:** End-to-end generation time (ms).
4. **Memory:** Peak RAM usage during inference (KB).

10.2 Baselines

1. **GPT-4 (API):** State-of-the-art LLM, cloud-based.
2. **CodeT5-small:** 60M parameter code model, no grammar constraints.
3. **GC-SLM (ours):** 15M parameters with grammar-guided decoding and S-LoRA.

10.3 Target DSL

We define a DSL for embedded control with the following constructs:

```
program     ::= statement+
statement   ::= assignment | conditional | loop | action
assignment  ::= IDENT '=' expression
conditional ::= 'when' condition ':' action
loop        ::= 'every' duration ':' action
action      ::= 'set' pin 'to' value | 'wait' duration
```

Listing 1: Example DSL grammar (excerpt)

The full grammar has 47 production rules.

11 Discussion

Limitations.

- **Semantic correctness:** Grammar constraints ensure syntax but not semantics. Future work should integrate type systems and runtime verification.
- **Grammar complexity:** Our analysis assumes LL(1)/LR(1) grammars. More complex grammars (e.g., context-sensitive) require different algorithms.
- **On-device deployment:** While GC-SLMs are small, deploying 15M parameters on a microcontroller remains challenging. We envision cloud-edge hybrid architectures or offline compilation.

Future Directions.

- **Quantization:** 4-bit quantization could reduce 15M parameters to <10MB.
- **Verification-in-the-loop:** Use formal verification as a reward signal during training.
- **Multi-DSL transfer:** Pretrain on multiple DSLs to enable rapid adaptation.

12 Related Work

Code Generation with LLMs. Codex [1], CodeGen [2], and StarCoder [3] demonstrate strong code generation but require billions of parameters. AlphaCode [12] combines LLMs with search but remains large-scale. Our work focuses on the small model regime (<50M parameters).

Constrained Decoding. PICARD [7] uses incremental parsing for SQL; Synchromesh [8] enforces type constraints. We extend these ideas to general CFGs with theoretical analysis.

Efficient Fine-tuning. LoRA [9], AdaLoRA [10], and QLoRA [11] reduce fine-tuning cost. Our S-LoRA introduces structured sparsity, further reducing parameters.

Embedded Systems Programming. Prior work on domain-specific languages for embedded systems includes Lustre [13], Esterel [14], and Céu [15]. These focus on language design rather than automated generation.

13 Conclusion

We presented Grammar-Constrained Small Language Models (GC-SLMs), a framework for generating domain-specific language code under strict resource constraints. Our contributions include:

1. A grammar-guided decoding algorithm with $\mathcal{O}(|G| + |\mathcal{V}|)$ overhead per token.
2. Sparse LoRA (S-LoRA), reducing adapter parameters by 60% with structured sparsity.
3. Theoretical bounds on model capacity and sample complexity for DSL generation.
4. A training pipeline combining template expansion, LLM bootstrapping, and manual curation.

GC-SLMs bridge the abstraction gap between human intent and embedded implementation, enabling automated code generation where LLMs are infeasible. This work lays the foundation for accessible programming of resource-constrained devices.

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