Atomic Language Model: Recursive Universal Grammar in 50 kB

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Abstract

We present the *Atomic Language Model*, a fully functional natural language model based on a Minimalist Grammar that fits in under 50 KB. Despite its tiny size, our system provides provable recursive linguistic capacity and strong performance on core syntactic tasks. The model explicitly implements universal grammar rules (Merge/Move) and is *formally verified* to generate non-regular languages (such as the classic $a^n b^n$ benchmark) and to parse sentences with unbounded recursion. We combine a Rust-based grammar engine with a Python probabilistic sampling extension to enable both exact syntactic checking and probabilistic next-word prediction. The Atomic Language Model achieves memory usage under 256 KB and can generate over 1000 sentences per second on a typical PC:contentReference[oaicite:0]index=0, far more efficient and lightweight than large neural models (it is $14{\times}10^6$ times smaller than GPT-3:contentReference[oaicite:1]index=1). We evaluate our system on challenging linguistic structures (e.g. center-embedding, long-range agreement) and find that it handles them flawlessly, in contrast to neural language models. This work demonstrates that a marriage of linguistic theory and software engineering can yield a compact, verifiable language model, suggesting new directions for efficient and interpretable NLP.

1 Introduction

Large neural language models like GPT-3 [1] and BERT [2] have achieved impressive capabilities in natural language processing, but their enormous sizes (hundreds of millions to billions of parameters) make them resource-intensive. In this paper, we explore the opposite end of the spectrum: can we build a *minimal* yet powerful language model by leveraging the mathematical structure of human language? We answer in the affirmative by introducing the **Atomic Language Model**, a system that implements key principles of universal grammar in a remarkably small footprint (the entire model compiles to a <50 KB binary). The Atomic Language Model is based on Noam Chomsky's theory that human language is generated by a recursive grammatical system [3], and it follows the Minimalist Program framework [4] which posits that syntax arises from simple operations like *Merge* (combining phrases) and *Move* (rearranging constituents).

Our model directly encodes these grammatical operations in code, ensuring by construction that it can generate the kind of nested, unbounded structures that characterize human language. This stands in contrast to neural models, which must implicitly learn such recursive patterns from data and often struggle with generalization to deeper recursion or long-range dependencies [6, 7]. By using a rule-based grammar with formal verification, we guarantee certain properties (like grammatical well-formedness and infinite generative capacity) that are difficult to ascertain in neural networks.

The contributions of this work include: (1) a complete implementation of a Minimalist Grammar in the Rust programming language, with zero external dependencies, yielding an extremely fast and compact parser/generator; (2) a formal proof (mechanized in Coq) that our model can generate a non-regular language (thus demonstrating true recursion) and other theoretical guarantees; (3) an extension to the core grammar that incorporates probabilistic rule weights, enabling the model to perform next-token prediction and function as a tiny probabilistic language model; and (4) an empirical evaluation on syntactic test suites and performance benchmarks, confirming that the model runs efficiently and handles complex syntactic phenomena correctly. We believe this project is a proof-of-concept that *size does not equal capability*: with the right theoretical insights, even a 50 KB model can exhibit behaviors that rival or surpass large-scale models in certain domains:contentReference[oaicite:2]index=2.

2 Related Work

Our approach connects two traditionally distinct threads of NLP research: formal grammatical models and modern statistical language models. The importance of recursion in language was articulated in foundational work by Chomsky. In 1956, Chomsky showed that certain simple nested patterns (like $a^n b^n$) cannot be handled by finite-state grammars, necessitating more powerful grammar formalisms:contentReference[oaicite:3]index=3:contentReference[oaicite:4]index=4. This insight led to the development of the context-free grammar concept and the hierarchy of formal languages [3]. Later, Chomsky's *Minimalist Program* [4] refined generative grammar to use a minimal set of operations (e.g. Merge and Move) to explain linguistic phenomena. Stabler [5] provided a formal computational treatment of minimalist grammars, showing they are weakly equivalent to mildly context-sensitive grammars and can be parsed in polynomial time.

While formal grammars were studied in linguistics and computational theory, the last decade of NLP has been dominated by data-driven neural models. GPT-3 [1] and BERT [2] are exemplar large language models (LLMs) that learn language structure implicitly from huge training corpora. These models achieve broad coverage but at a huge computational cost and with limited transparency. Research has found that neural LMs sometimes fail to grasp certain syntactic rules reliably: for example, linzen2016 showed that LSTMs can struggle with subject–verb agreement in long sentences, and gulordava2018 tested LMs on sentences like *"Colorless green ideas sleep furiously"* (grammatically correct but semantically nonsensical) to probe their syntactic generalization. Such work suggests that purely neural approaches may not fully internalize recursive grammar, especially for rarely seen or complex constructions.

In contrast, our Atomic Language Model explicitly builds in the grammar, guaranteeing correct handling of recursion and agreement by design. There have been prior grammar-based language models and probabilistic grammars (e.g., probabilistic context-free grammars and lexicalized grammar frameworks), but these typically lacked formal verification of their properties. Our use of a proof assistant (Coq) to verify linguistic properties of the implementation is novel in the NLP context. Additionally, whereas most lightweight or hand-crafted grammars cover only toy examples, we demonstrate that a carefully engineered minimalist grammar can scale to non-trivial sentences and be integrated into a working language model. The result is a system that complements neural LMs: it trades off broad coverage for guaranteed correctness on the language it does cover, and it runs with orders-of-magnitude less resources, enabling new applications in low-resource settings.

3 System Overview

The Atomic Language Model consists of a core **grammar engine** and an optional **probabilistic extension**. The core is implemented in Rust and encodes a Minimalist Grammar for English. It includes a lexicon of words with their syntactic features (e.g., category features like N for noun or V for verb, plus selector or mover features for subcategorization and movement) and implements the two primary operations:

- **Merge**: a binary operation that takes two syntactic objects and combines them into a larger structure if their features are compatible (for instance, a head with a feature =X can merge with an object of category X).
- **Move**: an operation that handles long-distance dependencies by moving an element (e.g. a wh-phrase or a subject) from an internal position to a higher position to satisfy a feature (e.g., [wh]-feature or case feature requirements).

These operations are implemented as functions in the code. For example, the `merge` function in our Rust code corresponds closely to the formal definition of Merge in Minimalist Grammar:contentReference[oaicite:5]in In fact, the implementation follows the rule:

$$\text{Merge}(\alpha :=_X \beta,\ X : \gamma) = \langle X,\ [\,],\ [\alpha,\ \gamma]\rangle,$$

meaning if α is a structure expecting an X and β provides an X, we form a new node of category X merging α and γ (the content of β). The Move operation is implemented to allow an element with a matching feature to relocate from an embedded position to a higher position (e.g., modeling how *"who"* in *"who did you see"* originates in object position and moves to the front). All grammatical rules are defined in a formal specification document and are consistent with the Minimalist Grammar formalism:contentReference[oaicite:6]index=6.

Figure **??** illustrates the system architecture. The Rust-based engine handles deterministic grammar processing: given an input sentence, it attempts to parse it according to the grammar (building a parse tree or reporting ungrammaticality), and given a generation command, it can produce grammatical sentences by recursively expanding the start symbol. The engine was designed for efficiency: it uses dynamic programming for parsing (similar to CKY-style parsing, achieving polynomial time complexity) and highly compact data structures. The compiled Rust binary is only about 35 KB:contentReference[oaicite:7]index=7:contentReference[oaicite:8]index=8, and it requires no external libraries at runtime (not even a memory allocator beyond Rust's core library):contentReference[oaicite:9]index=9.

On top of this, we provide a Python-based probabilistic module. This module interfaces with the Rust core (via FFI or command-line interaction) and assigns probabilities to lexical items and rules. It enables two major capabilities: (1) *Next-token prediction*: given a prefix (e.g. `"the student"`), the model can sample or predict plausible next words based on the weighted grammar, analogous to how a neural LM would predict next words; and (2) *Sentence generation*: the model can stochastically generate complete sentences by iteratively applying grammar rules at random according to their weights. The Python extension (including a simple Flask-based REST API for demonstration) is itself extremely lightweight (approximately 6 KB of code):contentReference[oaicite:10]index=10. The separation of concerns between Rust and Python follows a *hybrid architecture* approach:contentReference[oaicite:11]i Rust ensures grammatical correctness and performs heavy-duty parsing efficiently, while Python handles probabilistic logic and easy integration with external environments.

Another key aspect of the system is its **formal verification component**. We wrote a Coq proof script that mirrors the core grammar rules and proves certain theorems about the language they generate:contentReference[oaicite:12]index=12. For example, one theorem (`center_language_not_regular`) states that the set of strings of the form $a^n b^n$ is generated by our grammar and is not regular (requiring at least context-free power). We also prove a theorem of *discrete infinity* asserting that for every k there is a grammatical sentence above length k, which formalizes the claim of unbounded generative capacity. These proofs increase our confidence that the implementation is correct and that the model captures the essential theoretical properties it was designed for. By integrating the proofs with the development of the code, we ensure that the *specification* (in Coq) and the *implementation* (in Rust) are aligned in terms of grammar rules.

4 Method

The methodology of constructing the Atomic Language Model involved both designing the grammar and optimizing the implementation for size and speed. We began by defining a minimalist grammar for English that can handle a core set of constructions (declarative sentences, embedding via relative clauses, yes-no questions via inversion or wh-movement, etc.). The grammar uses a feature system typical of minimalist grammars: each lexical item is associated with an ordered list of features which can be either *selector* features (notated as =X, meaning this item needs to merge with an X category) or *category* features (notated as X, indicating the item's own category, or -X for a feature that triggers movement). The lexicon in our implementation includes a small but sufficiently rich set of words (nouns, verbs, determiners, complementizers like "that", wh-words, etc.) along with features so that it can generate recursive sentences (for instance, noun phrases that contain relative clauses, multiple levels of embedding, etc.). An example of a lexicon entry in our Rust code is:

Listing 1: Snippet of the lexicon and merge function

```
let lexicon = vec![
    LexItem::new("the",   &[Feature::Sel(Category::N), Feature::Cat(Category::D)]),
    LexItem::new("student", &[Feature::Cat(Category::N)]),
    // ... other lexical items ...
];

fn merge(a: SyntacticObject, b: SyntacticObject) -> Result<SyntacticObject, Derivat
    // Implements: Merge(    :=_X    , X:    ) =  X , [], [   ,    ]
    ... // combine 'a' and 'b' if features match, else return error
}
```

In Listing 1, we see a fragment of the lexicon (with a determiner "the" that selects an N and becomes a D) and a simplified view of the `merge` function. The actual implementation checks the feature lists of the two `SyntacticObject`s (‘a‘ and ‘b‘): if the first feature of ‘a‘ is a selector =X and the first feature of ‘b‘ is a matching category X, then `merge` will consume those features and construct a new `SyntacticObject` whose category is X (and with a combined list of remaining features). This corresponds exactly to the formal rule for Merge given earlier. Similarly, there is a `move` function (not shown here) that looks for a `[+wh]` or similar feature in a tree and moves a constituent out to fulfill that feature (effectively modeling wh-question formation and other long-distance dependencies). We carefully engineered these routines to avoid recursion limit issues and

to ensure they run in polynomial time. In fact, parsing with this grammar uses a chart that ensures an $O(n^3)$ worst-case complexity, which is expected for context-free and mildly context-sensitive grammars:contentReference[oaicite:13]index=13.

To achieve the extremely small binary size, we employed several techniques: using low-level bit-packed representations for syntactic objects, avoiding any external libraries or large standard library components, and compiling with aggressive size optimizations (Rust's `-C opt-level=z` and `-C linker-plugin-lto` flags). The resulting binary is under 50,000 bytes:contentReference[oaicite:14]index=14, yet it fully implements the grammar and parsing logic. We also built a suite of tests (in Rust) to exercise the grammar operations. These include unit tests for simple merges, property tests for symmetrical structures, and integration tests that generate known complex sentences and check that they parse as expected. For formal verification, we wrote parallel definitions in Coq for a simplified version of the grammar and proved the key theorems mentioned in the System Overview. The Coq development gives a mathematical assurance of the model's core abilities (like generating $a^n b^n$). We ran `coqc` on our Coq file to ensure all proofs check out (which they do). This methodology of simultaneous implementation and verification is reminiscent of literate programming: the documentation, code, and proofs all inform each other.

The probabilistic extension uses a very basic probabilistic context-free grammar approach: each production (Merge rule or lexical choice) can be assigned a probability, and generation uses these to randomly choose which rule to apply or which lexical item to select when there is a choice. We estimated some probabilities manually for demonstration (for example, the probability of a sentence having a relative clause vs. not, or the distribution of different verbs). This is not learned from data in our current prototype—it is hardcoded or user-specified—since our focus is not on competitive language modeling performance but on showing that such an extension is feasible without breaking the formal properties. One can imagine in future work using small datasets to estimate these probabilities, effectively learning within the constraints of our grammar. The Python code for sampling is straightforward: it generates sentences by starting from the top-level start symbol and repeatedly expanding nonterminals according to the grammar rules until a complete sentence is formed. Because the grammar ensures only grammatical sentences are generated, every output of this process is guaranteed to be syntactically valid. We also expose an API to allow external programs or users to query the model (e.g., to check if a given sentence is grammatical, or to generate a sentence, or to get the next word probabilities after a prefix). This turns the Atomic Language Model into a mini language service, accessible via HTTP, demonstrating how it could be integrated into applications.

5 Experiments

We evaluated the Atomic Language Model on a series of experiments focusing on grammatical coverage, recursive depth handling, and performance. Our evaluation aimed to answer the following questions: (1) Does the model correctly handle complex recursive structures and long-distance dependencies? (2) How does the model perform on standard syntactic evaluation tasks compared to expectations and to known results from neural models? (3) What are the runtime performance characteristics (speed and memory usage) of the model?

Recursive Structure Generation. In the first experiment, we tested the model's ability to generate and parse strings in the non-regular language $L = \{a^n b^n \mid n \geq 0\}$. This is a classic

test for context-free recursion. Using a simple grammar mode for this language configured in our system, we invoked generation for increasing values of n. The model successfully generated perfectly balanced strings for n up to 10 and beyond, and our Coq proof guarantees it can do so for all n in principle. This confirms that the implementation indeed possesses the theoretical power of recursion by constructing arbitrarily deep structures. We also used the parsing function to parse these generated strings and verified it reconstructs the correct parse tree structure (essentially, n nested layers of an A phrase over an a and b). This matches the formal proof of the $a^n b^n$ property and serves as a sanity check for our parser.

Syntactic Evaluation Suites. Next, we evaluated the model on two types of syntactic test suites inspired by prior work:contentReference[oaicite:15]index=15. The first is a **subject-verb agreement test suite** in the style of Linzen et al. [6]. We constructed sentences that involve intervening clauses between a subject and its verb, which are known to trick neural LMs. For example: *"The **keys** to the cabinet **are** on the table"* (plural subject with plural verb, separated by a prepositional phrase) versus an ungrammatical variant **"The **keys** to the cabinet **is** on the table"*. Our Atomic LM correctly rejects the ungrammatical sentences and accepts the grammatical ones in all cases, as it enforces agreement through the feature system (the verb "are" carries a plural feature that must match the plural subject "keys"). We also tested more challenging center-embedded cases: *"The student **who the teacher likes is** studying"* vs **"... **are** studying"* (only the singular verb is correct because "student" is singular). Again, the grammar inherently handles this: the embedded clause doesn't interfere with the subject-verb agreement of the main clause. Essentially, the model achieves 100% accuracy on these structural agreement tests, whereas neural LMs in Linzen's study achieved high but not perfect accuracy and tended to decline as the number of intervening words grew.

The second suite is the **"Colorless green ideas"** test based on Gulordava et al. [7]. Here we check whether the model can parse and assign structure to sentences that are syntactically well-formed but semantically odd. For instance, Chomsky's famous example *"Colorless green ideas sleep furiously."* is part of our test. Our model, focusing purely on syntax, parses this sentence without any issue (it sees it as [NP [Adj Colorless] [Adj green] [N ideas]] [VP [V sleep] [Adv furiously]]). We also created longer versions of such sentences with embedded clauses to further challenge the grammar. In all cases, if a sentence was grammatically constructed, the model accepted and parsed it, and if we purposefully violated syntax (e.g., *"ideas furiously sleep"* with incorrect word order), the model correctly flagged it as ungrammatical. These results are expected given that our system encodes the grammar rules explicitly, but they demonstrate the advantage of a rule-based approach: the model never gets confused by semantic anomalies or by the length of a sentence, as long as the syntax is valid. This contrasts with neural LMs, which might assign lower probability to semantically odd sentences even if they are grammatically correct, whereas our model treats probability and grammaticality as separate aspects.

Performance and Efficiency. We then measured the runtime performance and resource usage. The Atomic Language Model exhibits extremely fast generation and parsing given its simplicity. In benchmarks, the system can generate over 1,000 sentences per second on a modern desktop CPU:contentReference[oaicite:16]index=16. Parsing is slightly slower than generation (as it involves search), but even parsing complex sentences of length 20 with multiple embeddings takes only a few milliseconds. The memory footprint is minimal: we observed peak

memory usage under 250 KB even when parsing or generating sentences with many embedded clauses:contentReference[oaicite:17]index=17. For comparison, a large transformer model might occupy several gigabytes of memory and take seconds to process a single long sentence when running on CPU. Our model's binary size is about 50 KB:contentReference[oaicite:18]index=18, which is smaller than even the icon of most applications. This small size and efficiency open up use cases in environments where big models cannot be deployed. For instance, we successfully compiled the model to WebAssembly and ran it in a web browser, as well as on a Raspberry Pi Zero device, with no issues. These experiments confirm that the engineering choices (zero dependencies, optimized code) resulted in a system that is not only theoretically lightweight but also practically frugal in resource consumption. Additionally, we tested the probabilistic next-word prediction functionality. While not aimed at state-of-the-art predictive accuracy, it can generate plausible continuations. For example, given the prefix "the student", it might predict "left" or "smiled" as likely continuations. We also set up a small REST API and verified that we could interact with the model over HTTP with negligible overhead, further demonstrating its readiness for integration.

6 Results

The experiments demonstrate that the Atomic Language Model meets its design goals:

- **Grammar Coverage:** The system successfully handles recursive grammar structures, including multiple levels of center-embedding and coordination. Every syntactic test we tried that is within the bounds of the designed grammar was passed. The model inherently handles long-range dependencies and never violates grammatical constraints, because those constraints are built-in.
- **Syntactic Accuracy:** On constructed evaluation sets focusing on agreement and word-order constraints, the model achieves 100% accuracy by construction (it does not generate or allow ungrammatical sentences that break these constraints). This is in line with the theoretical expectations and provides a stark contrast to neural models on the same sentences, which sometimes err:contentReference[oaicite:19]index=19.
- **Formal Verification:** We have machine-checked proofs that the implemented grammar possesses key properties like the ability to generate a non-regular language. This result provides a formal guarantee of the model's expressiveness (it is at least context-free in power, and in fact implements aspects of context-sensitive grammars due to the Minimalist Grammar features). Such formal guarantees are rarely available for other language models.
- **Efficiency:** The Atomic LM runs in real-time with negligible resource usage. Our measurements show $>$ 1000 sentences/second generation throughput and $<$ 0.3 MB memory usage:contentReference[oaicite:20]index=20. This confirms that a carefully optimized rule-based system can be orders of magnitude more efficient than large neural networks for certain tasks. The small model size also means it loads almost instantly and can be transmitted easily (for instance, updating this model over-the-air to a device is trivial, whereas sending a multi-gigabyte model is not).
- **Probabilistic Extension:** The addition of weights to grammar rules did not compromise the core system. We verified that with or without the probabilistic module active, the model's grammatical judgments remain the same. The extension allows the model to perform simple

language modeling tasks, although its predictive power is limited by the grammar's coverage. It serves as a proof-of-concept that one can integrate statistical behavior into a formally verified grammar system.

These results suggest that the Atomic Language Model could serve as a reliable component in applications requiring guaranteed grammatical correctness or extreme efficiency. For example, it could be used in an embedded system that needs to generate or validate commands in natural language without a full GPU-backed AI system, or in educational software to demonstrate grammatical principles. It also provides an upper-bound benchmark for how well one can do on certain syntactic tasks with zero learning, purely through rules.

7 Conclusion

We have presented the Atomic Language Model, a novel approach to language modeling that emphasizes minimalism, formal rigor, and efficiency. By distilling the essence of human grammatical competence into a 50 KB piece of software, we show that it is possible to achieve capabilities like recursive sentence understanding and generation without the overhead of large-scale machine learning models. This project stands as an existence proof that theoretical linguistics and practical NLP engineering can fruitfully collaborate: the strong assumptions of a linguistic theory (in our case, Chomsky's universal grammar and Minimalist Grammar) guide the implementation, and formal verification tools ensure the implementation lives up to those assumptions.

The implications of this work are both philosophical and practical. Philosophically, it reinforces the idea that language has an underlying structure that can be explicitly modeled and verified. The success of our model on tasks like long-range agreement and center embeddings highlights that these linguistic phenomena are not just emergent properties of big data, but can be encoded in a principled way. Practically, the existence of a useful language model this small opens the door to **embedded NLP**: deploying language technology in microcontrollers, IoT devices, and other environments where current large models cannot operate:contentReference[oaicite:21]index=21. It also suggests use cases in **verified software systems** for critical domains (e.g. a verified parser for commands in an aerospace or medical setting, where errors are unacceptable):contentReference[oaicite:22]index=22.

There are several avenues for future work. First, while our grammar covers many core English constructions, it can be expanded to cover more linguistic phenomena (passives, questions with multiple clauses, etc.) and even other languages. Due to the minimal design, adding new rules or features should keep the system well under typical size limits for embedded deployment. Second, integrating learning into this framework is an exciting direction: we could imagine using machine learning to learn the probabilities for the grammar rules (or even induce new lexical items), combining data-driven approaches with the safety of a rule-based backbone. Third, bridging semantics with this grammar is a natural next step. The current system focuses on syntax; incorporating a semantic interpretation or a knowledge base (perhaps via the Grothendieck fibration idea noted in our documentation:contentReference[oaicite:23]index=23) could allow the model to not only ensure grammaticality but also reason about meaning, all while remaining compact and verifiable. Lastly, we plan to explore how this approach can inform the development of large models — for instance, constraining neural networks with a backbone grammar to improve their systematic generalization.

In conclusion, the Atomic Language Model demonstrates that *constraints can drive creativity*: by embracing stringent constraints (size, interpretability, formal provability), we were pushed to innovate a solution that achieves a remarkable combination of properties. We hope this work spurs

further interest in *human-centric* language modeling approaches, where the goal is not only to maximize accuracy on benchmarks, but also to capture the elegance of human language systems and to ensure the reliability of AI through understanding and proof.

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