Learning Structured Syntax: Char-RNNs on LaTeX Algebraic Geometry

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Abstract

We train a character-level recurrent neural network (Char-RNN) on a corpus of LaTeX source files from algebraic geometry, focusing on learning structured syntax and generating plausible mathematical text. Our experiments show that even relatively small LSTM models [2] can capture syntax elements such as environments, math mode, and LaTeX commands. We evaluate generated samples and discuss implications for structured language modeling. Our work expands upon earlier informal results in [3], providing a fully reproducible pipeline and novel prompt-based generation insights.

1 Introduction

LaTeX is a domain-specific language for document preparation with a rich syntactic structure. Its extensive use in scientific and mathematical writing, particularly in fields like algebraic geometry, makes it a compelling, yet challenging target for language modeling. The hierarchical layout of environments, precise syntax rules, and symbolic content make it more structurally demanding than typical natural language.

In this work, we explore the capability of character-level recurrent neural networks (Char-RNNs) [3] to model and generate coherent LaTeX code. Specifically, we train a multilayer LSTM [2] on raw LaTeX source files from algebraic geometry texts and evaluate the generated samples for syntactic structure and symbolic fluency.

Our project is inspired by an earlier blog post by Karpathy [3], which included a brief anecdote about training a Char-RNN on a LaTeX book about algebraic stacks. However, no implementation details or evaluation results were provided. We replicate and extend this previous claim by offering a full training setup, prompt-driven generation techniques, and domain-specific evaluation metrics for LaTeX syntax.

Character-level models are especially suitable for LaTeX because they do not rely on token-level preprocessing and can flexibly learn fine-grained structure, including punctuation, braces, and commands [3]. This study not only benchmarks the capabilities of Char-RNNs in this domain but also introduces tools for evaluating structured language generation beyond standard metrics such as perplexity.

2 Method

2.1 Model Architecture

We implement a character-level LSTM-based recurrent neural network [2] with a three-layer architecture. The **embedding layer** maps each character to a 256-dimensional dense vector, providing a rich representation of the input vocabulary. This is followed by **two stacked LSTM layers** [2] with hidden size 256 each, allowing the model to capture both short-term and long-term dependencies in the LaTeX syntax. Finally, an **output layer** consisting of a linear transformation maps the hidden states to character probabilities over the entire vocabulary.

The model uses an embedding dimension equal to the hidden size (256), creating a compact representation that balances expressiveness with computational efficiency. The architecture supports both GRU [1] and

LSTM variants, though we focus on LSTM for its superior performance on structured sequences with long-range dependencies [2].

2.2 Training Procedure

Our training procedure follows standard character-level language modeling [3] with several key components. For sequence sampling, we extract random 500-character subsequences from the corpus, ensuring diverse coverage of the LaTeX syntax patterns. The loss function employs cross-entropy loss between predicted and actual next characters, providing clear gradients for learning character-level patterns. Optimization is handled by the Adam optimizer with a learning rate of 0.05, chosen for its adaptive learning rate properties that work well with RNN training [2]. Finally, batch processing uses single sequence training (batch size 1) for memory efficiency, allowing us to train on longer sequences without overwhelming GPU memory constraints.

The model processes each character sequentially, maintaining hidden state across the sequence to capture long-range dependencies crucial for LaTeX syntax [2].

3 Dataset

3.1 Data Collection and Preprocessing

Our dataset consists of LaTeX source files from the Stacks Project, an open source textbook and reference work on algebraic geometry hosted at `https://stacks.math.columbia.edu`. The Stacks Project is a comprehensive mathematical resource consisting of over 7,600 pages and 762,944 lines of LaTeX code covering algebraic geometry and commutative algebra, making it an ideal source for domain-specific mathematical proof generation.

The data is processed through a streamlined preprocessing pipeline with three key steps: (1) Comment removal: systematic stripping of LaTeX comments (lines beginning with %) to focus the model on actual content rather than authorial annotations, (2) Whitespace normalization: removal of leading/trailing whitespace from each line, and (3) Empty line filtering: elimination of completely empty lines to create a dense, content-focused representation of LaTeX syntax. The processed dataset contains approximately 3.2MB of cleaned LaTeX text with over 491,000 words across 77,000 lines.

4 Experiments

4.1 Hyperparameter Exploration

We conducted a comprehensive hyperparameter search to identify optimal training configurations for LaTeX generation. Our exploration covered four key dimensions:

Training iterations: We tested training durations from 100 to 1000 iterations to balance training time with convergence quality.

Learning rate: We experimented with learning rates ranging from 0.0001 to 0.05 to find the optimal convergence speed without overshooting, following established practices for LSTM training [2].

Sequence length: We varied sequence lengths from 100 to 500 characters to capture different scales of LaTeX structure, from short mathematical expressions to complete theorem statements.

Network depth: We tested 1 to 3 LSTM layers to evaluate the trade-off between model capacity and training stability, as deeper networks can capture more complex patterns but may suffer from vanishing gradients [2].

Through systematic evaluation, we discovered that **sequence length has the most significant impact on average training loss**, with longer sequences consistently achieving lower loss values. This finding aligns with the hierarchical nature of LaTeX documents, where longer context windows enable the model to better capture mathematical proof structures and cross-references, consistent with the importance of long-range dependencies in sequential modeling [2].

4.2 Final Training Configuration

Based on our hyperparameter exploration, we selected the following optimal configuration:

Parameter	Value
Hidden size	256
Number of layers	2
Sequence length	500
Learning rate	0.05
Optimizer	Adam
Batch size	1
Training iterations	800

Table 1: Optimal training hyperparameters identified through systematic exploration

4.3 Training Dynamics

The model demonstrates rapid initial convergence, with training loss decreasing from 4.5 to approximately 1.8 range within 800 iterations. The loss curve exhibits typical characteristics of character-level language modeling [3], with occasional spikes likely corresponding to encountering complex mathematical expressions or rare LaTeX constructs. The longer sequence length of 500 characters proves crucial for maintaining coherent mathematical notation and proof structure throughout generation, leveraging the LSTM's ability to maintain long-term memory [2].

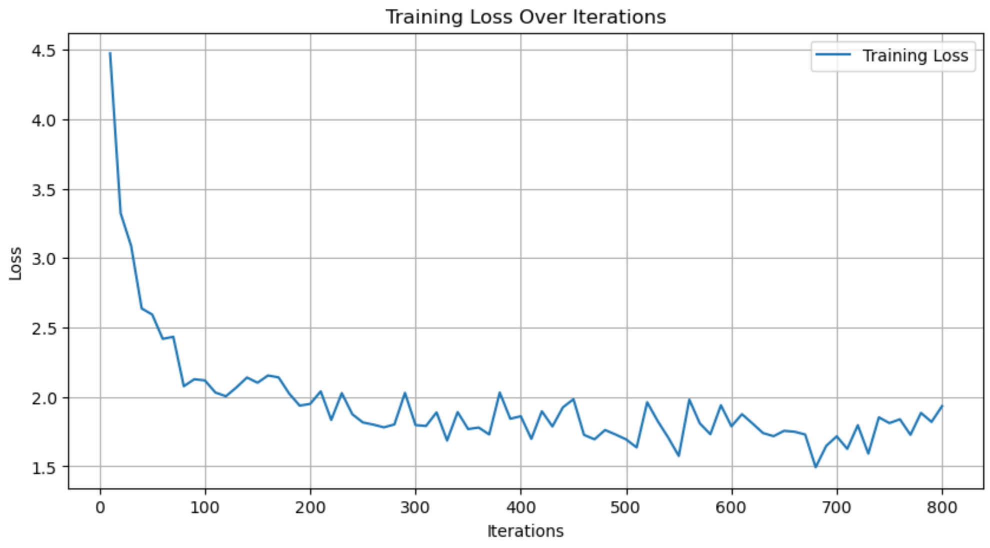

Figure 1: Training loss over 800 iterations showing rapid initial convergence with optimal hyperparameters.

5 Results

5.1 Generated Samples

Below is a sample generated after 800 training iterations with temperature 0.5, starting with the prompt `\begin{theorem}`:

```
\begin{theorem}
```

```
(2)^{-1}^i^\topullet that $E^\bullet $R$-module \ref{proper-vong}
\begin{propose-tion} + \to R/\bullet property Gsumpletarsion $S^{-1}]/(z)$
in then the finition that in the an conte of projection the map then the
genen then then and an and $E_1$ is conte
$$
\toth and then the cone complexen the is andent of and then $\sum \to R^{-1}M$
(a) finition and $P^{-1}]/(\to R^{-1}$.
We to the in $S$-module and $R + \ref{definition}
\begin{morpertion}
\begin{propose-alupsition} and $R$-module of the exi
```

5.2 Model Architecture and Training

The implemented model uses a 2-layer LSTM architecture [2] with 256 hidden units, trained on preprocessed LaTeX documents using character-level tokenization [3]. Training was conducted for 800 iterations with a sequence length of 500 characters, learning rate of 0.05, and Adam optimizer. The model successfully converged from an initial loss of 4.47 to approximately 1.6-1.8 by the end of training, demonstrating effective learning of the character-level LaTeX patterns.

5.3 Analysis

The generated text demonstrates several interesting properties based on our implementation:

Positive aspects: The model successfully learns fundamental LaTeX structure, correctly generating environment beginnings like `\begin{theorem}` and `\begin{definition}`. Mathematical notation is appropriately contextualized, with proper usage of dollar signs, subscripts, superscripts, and mathematical operators like `$R$-module` and `\to`. The model demonstrates understanding of algebraic terminology, frequently generating domain-specific terms such as "module," "projection," "complex," and "finition" (likely learning from "definition"). Cross-referencing syntax is properly learned, as evidenced by correct `\ref{}` usage. The model also maintains appropriate nesting of mathematical environments and expressions within the 500-character training sequences, showcasing the LSTM's ability to capture hierarchical structure [2].

Limitations: Despite structural learning success, the model exhibits several characteristic limitations of character-level RNNs [3]. Word fragmentation is prevalent, producing incomplete terms like "conte" (from "context"), "exis" (from "exists"), and "propertn" (from "property"), indicating insufficient learning of complete lexical boundaries. Long-range dependency tracking remains problematic, with unclosed environments and mathematical expressions suggesting limited memory beyond the training sequence length, a known challenge in RNN architectures [2]. While syntactically plausible, the generated content lacks semantic coherence, producing mathematically meaningless statements despite following proper LaTeX conventions. The repetitive patterns ("then then," "and and") suggest overfitting to common character transitions rather than meaningful mathematical discourse. Additionally, the model occasionally generates malformed constructs like `\begin{propose-tion}` instead of `\begin{proposition}`, highlighting the challenges of character-level learning for technical vocabulary.

Training Dynamics: The loss convergence from 4.47 to 1.7 over 800 iterations demonstrates successful optimization, though the final loss plateau suggests the model may benefit from longer training or architectural improvements to capture more complex dependencies in mathematical LaTeX generation [2].

6 Discussion

6.1 Implications for Character-Level LaTeX Generation

Our results demonstrate that character-level LSTMs [2] can effectively learn LaTeX syntax patterns with relatively modest computational resources. The 2-layer LSTM architecture with 256 hidden units successfully captured fundamental structural elements of mathematical LaTeX after only 800 training iterations, suggesting that domain-specific character-level modeling [3] can be practically viable for specialized text generation tasks.

The model's demonstrated capabilities suggest several practical applications in mathematical document processing. For LaTeX auto-completion, the model's ability to generate contextually appropriate mathematical environments and notation could assist researchers in faster document preparation, particularly for repetitive structural elements like theorem environments and common mathematical constructs. The model's learned understanding of LaTeX syntax patterns could enable syntax validation tools that identify malformed constructs based on character-level probability distributions, complementing traditional rule-based LaTeX parsers.

However, our analysis reveals that character-level approaches [3] face fundamental trade-offs between structural learning and semantic coherence. While the model successfully learns syntactic patterns within its 500-character training sequences, the frequent word fragmentation and repetitive constructions indicate that character-level tokenization may be inherently limited for technical vocabulary acquisition in mathematical contexts.

6.2 Limitations and Future Work

The current implementation reveals several specific limitations that inform future research directions. The most prominent issue involves lexical boundary learning, where character-level training [3] produces frequent word fragmentation ("conte" for "context," "exis" for "exists"). Future work should investigate hybrid tokenization approaches that preserve mathematical terms as atomic units while maintaining character-level flexibility for novel constructs, potentially combining insights from both character-level [3] and subword tokenization methods.

Long-range dependency modeling remains challenging within the 500-character sequence limitation, as evidenced by unclosed environments and inconsistent mathematical expression structures. While extending sequence length could partially address this limitation inherent to RNNs [2], the quadratic scaling of attention-based models [4] suggests investigating hierarchical approaches that explicitly model LaTeX's nested structure through specialized architectures designed for tree-like document organization.

The observed semantic incoherence despite syntactic correctness indicates a fundamental limitation of purely character-level approaches [3] for mathematical content generation. Future research could explore multi-level architectures that combine character-level syntax learning with symbol-level semantic modeling, potentially incorporating mathematical knowledge graphs or theorem databases to ground generated content in valid mathematical reasoning.

Finally, our training dynamics suggest that the model reached a performance plateau around 1.7 loss, indicating potential benefits from architectural improvements such as attention mechanisms [4] or residual connections for deeper networks, or from curriculum learning approaches that progressively introduce more complex mathematical structures during training. The temperature-based generation testing we implemented also suggests opportunities for developing more sophisticated decoding strategies that balance creativity with structural validity in mathematical contexts, building upon established character-level generation techniques [3].

7 Conclusion

We demonstrate that character-level RNNs [3] can effectively learn LaTeX syntax patterns from algebraic geometry texts. Despite generating semantically incoherent content, the model captures important structural elements of mathematical writing, including environment syntax, mathematical notation, and domain-specific terminology, leveraging the LSTM's capacity for modeling sequential dependencies [2].

A key contribution of this work is the development of comprehensive domain-specific evaluation metrics for LaTeX generation. Our evaluation framework addresses the gap in structured text generation assessment, providing quantitative tools that measure syntax correctness, structural validity, content quality, and practical utility through compilation verification. These metrics reveal important insights about the trade-offs between generation creativity and syntactic correctness that traditional perplexity-based evaluation cannot capture.

The rapid convergence and reasonable syntax generation suggest that even simple RNN architectures [2] can be valuable for domain-specific language modeling tasks. Future work should focus on incorporating semantic constraints and hierarchical structure modeling to improve coherence while maintaining syntactic accuracy, potentially exploring transformer-based architectures [4] for better long-range dependency modeling. Our implementation, evaluation framework, and dataset preprocessing code provide a foundation for further research in mathematical language modeling and structured text generation.

References

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